Bank Value Creation, Intermediation and Managerial Ability

ROBEJSEK, PETER,PAUL

Durham University Business School
Department of Economics and Finance

Bank Value Creation, Intermediation and Managerial Ability

A Thesis Submitted in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

Author:
Peter Paul Robejsek

Supervisors:
Dr. Dennis Philip
Dr. Panayiotis Andreou

October 2014

Bank Value Creation, Intermediation and Managerial Ability

Abstract

Research in banking assumes that the production function is either parametric or deterministic in nature. This thesis develops a novel method for the parametrization of efficient frontiers, generalized frontier analysis (GFA), which uses artificial neural networks and the theory of asymmetric loss functions from forecasting to relax these assumptions. Results show that GFA can validly parametrize cost- and shareholder value efficiency (SHVE). This thesis also validates the SHVE concept by demonstrating that SHVE scores are more informative than managerial ability in explaining bank value creation.

Moreover, the work examines conflicting theoretical predictions about the relations between opacity, fragility and bank intermediation. These are disentangled using measures of bank opacity and liquidity creation from the recent literature. Since available opacity and liquidity creation proxies may not be mutually exclusive, there is the danger of obtaining trivial regression coefficients. Therefore this thesis focuses on intermediation quality, which is operationalized using efficient frontiers. Results show that both opacity and fragility improve the intermediation quality of banks.

Finally, this thesis investigates whether and how bank intermediation activity and managerial ability are related. This thesis hypothesizes, and the data supports, the notion that more able bank managers are both better liquidity creators and more avid risk takers. In addition, the interaction of liquidity creation and managerial ability in crises has thus far not been addressed. While empirical studies suggest that liquidity creation may increase during crises, theory predicts that it may be optimal for banks to reduce intermediation. Analysis shows that more ably managed banks reduce intermediation and risk during the financial crisis as hypothesized.

Overall, this thesis contributes to the banking and efficiency literatures by shedding light on heretofore unaddressed questions regarding the intermediation, managerial ability, shareholder value efficiency and opacity of banks and by developing a new method for the parametrization of efficient frontiers.

To all my teachers

Acknowledgements

This thesis is the product of a challenging and tremendously rewarding period of intense study. As such, this work would not have been possible without the help of a number of important people.

First, I wish to thank my supervisors, Dr. Dennis Philip and Dr. Panayiotis Andreou. The literal translation of the German term for PhD supervisor is “doctor father”. Rarely has this term, with all its positive connotations, been as fitting as in the case of my supervisors. Thus I wish to express my deepest gratitude to my “doctor fathers” for their support, both intellectual and emotional, and for giving me the amazing opportunity to learn from them.

The support that I have received from Ann, my partner, has been exceptional. She has patiently accepted my almost constant preoccupation with this thesis, never once grumbling and always providing moral support when I most needed it.

Many of the challenges related to this thesis were computational in nature. Overcoming these would not have been possible without the support of the DBS IT department, especially Ben Leighton, and the Durham HPC cluster, especially Henk Slim.

Furthermore, I have benefitted from the support of many friends in Durham and abroad. They have been encouraging and supporting me along the way. Most notably, I thank Fawad Mohammadi for frequent and stimulating discussions. Moreover, I owe a special debt of gratitude to Elisabeth Fisher and Waltraut Kuffner, aka “auntie”.

Last, but certainly not least, I wish to thank my parents without whose wholehearted and unquestioning support neither the first nor the last step towards the completion of this thesis could ever have been taken. They were the first to encourage my love of books and learning and I owe to them the possibility to undertake this work.

Peter P. Robejsek

Declaration

This is to certify that the material contained in this thesis has not been submitted in support of an application for another degree or qualification at this or any other University.

The copyright of this thesis rests with the author. No quotation from it should be published without the author's prior written consent and information derived from it should be acknowledged.

Contents

List of Figures

List of Tables

1. Introduction

The recent financial crisis has once again demonstrated the complexity of the banking industry. Furthermore, the resulting shortage of intermediation activity has also highlighted the importance of banks for the wider economy. However, many questions related to the banking sector have either not been resolved satisfactorily or have not been addressed at all in the literature. Some of these issues, such as the estimation of bank efficiency, are methodological in nature. Other issues are raised by the intermediation activity of banks and their transparency to outsiders, while yet other unexplored questions relate to the impact that managerial ability has in the context of intermediation and bank value creation. This thesis contributes to the banking literature by addressing some of the important extant issues.

While it is not the objective of this thesis to study problems of agency theory, the abundant banking literature related to agency problems provides a suitable motivation for part of the work carried out in this thesis. Agency theory suggests that there is no natural alignment between the interests of the owner and manager of an enterprise. While the owner is primarily interested in the maximization of value, the manager's target function may well contain subjective components such as job security, perquisite income and prestige (Jensen and Meckling, 1976, Myers, 2001). Numerous studies in the banking literature have investigated the extent to which manager and shareholder interests are aligned. Since the extent of this alignment is latent, a suitable proxy variable needs to be defined in any empirical investigation. Many studies use efficiency scores as indicators of agency cost, often with mixed results. For example, Mester (1993) and Altunbas, Evans and Molyneux (2001) use cost efficiency to proxy for the extent of agency costs and conclude that, in their samples, agency effects are not significant. On the other hand, DeYoung, Spong and Sullivan (2001), Berger and Bonaccorsi di Patti (2006) and Chortareas, Girardone and Ventouri (2011), also using efficiency to capture the extent of the misalignment of owner and manager interests, find support for hypotheses of the agency cost type.

This brief discussion illustrates that the literature finds contradictory results when testing hypotheses about bank behavior using efficiency scores.[1] These disparate findings could be due to a number of reasons. First, the literature investigates concerns about the misalignment of manager and shareholder interests. However, it uses conventional measures of efficiency, such as cost or profit efficiency, to operationalize the extent of this misalignment. Yet it is clear that a bank can be quite cost efficient, for instance, while not producing a great deal of value. However, value creation constitutes one of the primary motives of owners. Hence an alternative measure of efficiency, that can better quantify the target function of owners and thus better capture the extent of agency effects, may be needed. Second, the use of conventional efficiency measurement methods, such as data envelopment analysis (DEA) or stochastic frontier analysis (SFA), may not do justice to the underlying data generating process. This is because, as will be discussed in Sections 2.1.1 and 2.1.2, both these methods impose critical assumptions on the problem under investigation. Hence an alternative method of efficiency measurement may be required. Third, the largely agency-theoretic perspective of the above literature ignores the possibility that managers may be an idiosyncratic influence on the performance of banks. But in reality, as formalized for example in Hambrick and Mason's (1984) theory of upper echelons, the ability of managers may play an important part in explaining the performance of banks in general and therefore also their efficiency in particular. Hence the influence of managers may need to be explicitly controlled for.

An important step towards resolving the above issues has been taken in a recent contribution by Fiordelisi (2007), which develops the measure of shareholder value efficiency (SHVE). His work shows that the distance of banks from a stochastic "value creation frontier" can explain a large part of the overall variation in the value creation of European banks and Fiordelisi and Molyneux (2010) show that its dynamics respond to similar value drivers as value creation itself. This measure addresses the first point made above in that it provides an indicator of bank performance that aligns better with the target function of owners. However, even though SHVE is an important indicator of bank performance, the idiosyncratic influence of managers on the strategy and behavior of the bank might reduce its value as an explanatory variable. In addition, the appropriateness of stochastic frontier analysis as the estimation method used to parametrize SHVE has as yet not been assessed. This is, however, an important step towards ensuring the validity of the SHVE concept because, thus far, no rigorous

[1] Although only findings relating to the "agency cost hypothesis" are explicitly discussed above, a number of other hypotheses is studied in this literature with similarly conflicting findings. For contrary results concerning the "quiet life hypothesis" consider for example Chortareas, Girardone and Ventouri (2011) and Casu and Girardone (2009) as well as Casu and Girardone (2006).

theory is available to provide intuition as to the functional form underlying the creation of value in banks. Finally, because efficiency is a latent concept, the literature suggests that different parametrizations of efficiency should be validated by examining them for plausibility and comparing them against one another (see for example Bauer, Berger, Ferrier and Humphrey, 1998). This validation exercise is also as yet pending when it comes to SHVE since, as will become apparent, the use of the natural alternative estimation method, DEA, is not feasible.

These three issues are addressed in the first empirical chapter of this thesis (Chapter 3). Specifically, Section 3.2 develops a novel efficiency parametrization method, generalized frontier analysis (GFA), which relaxes the undesirable assumptions underlying DEA and SFA. Once this method is available, it is used to parametrize shareholder value efficiency as well as cost efficiency for a large sample of the US banking population. The resulting efficiency scores are then investigated on a set of plausibility criteria in order to examine whether the new method can validly parametrize efficiency scores. Results show that this is in fact the case. Furthermore, SHVE scores obtained from SFA and GFA are compared in regression analyses in terms of their explanatory power with respect to bank value creation. Results show that SFA and GFA are complementary indicators of bank efficiency. However, GFA strongly outperforms SFA in terms of the economic and statistical informativeness of the resultant SHVE scores. Furthermore, SHVE is shown to be more important than managerial ability in explaining value creation. Thus Chapter 3 provides strong evidence that GFA is a promising, flexible efficiency parametrization method, which does not suffer from the methodological problems of the more traditional approaches. Moreover, these results further validate Fiordelisi's (2007) SHVE concept and suggest that future research, investigating for example agency problems, would do well to embrace this measure.

A crucial feature of banks is their provision of intermediation services to the wider economy (see for example Diamond and Dybvig, 1983). Nevertheless, primarily due to an absence of an acceptable operationalization of this aspect of bank behavior, the quantity and quality of these services has, until recently, not been investigated thoroughly. However, recent research has provided efficacious measures of bank liquidity creation and thus opened the avenue for further inquiry (see for example Berger and Bouwman, 2009). More specifically, a classification of bank assets and liabilities according to their marketability, together with heuristically selected weights, enables one to compute the liquidity creation of banks. This measure has been shown to reflect bank behavior during crises (Berger and Bouwman, 2008), to capture value relevant behavior

(Berger and Bouwman, 2009) and to be responsive to regulatory intervention (Berger and Bouwman, 2012).

The empirical literature has collated evidence that banks are opaque (see for example Morgan, 2002 and Flannery, Kwan and Nimalendran, 2013). This feature of banks is believed to emanate from the nature of their assets. These are opaque to outsiders precisely because of the role of the intermediary as, for example, a delegated monitor (Berger and Bonaccorsi di Patti, 2006). However, the impact of opacity on bank intermediation has, thus far, not been investigated. Moreover, a strand of the theoretical literature has suggested that bank risk is intrinsically related to the intermediation activity of banks (see for example Diamond and Rajan, 2001). Specifically, this theory argues that more fragile banks are more effectively disciplined by the threat of a bank run, which would cause them to lose their valuable license. However, alternative models that consider soft budget constraints predict that bank intermediation activity is negatively associated with bank riskiness (consider for example Berglöf and Roland, 1997). In addition to these conflicting predictions about risk and intermediation, these theories allow for the prediction that opacity will be conducive for bank intermediation activity. Such a view is disputed by the theory of Coval and Thakor (2005), however. This leads to three conflicting hypotheses about the interplay between bank fragility, opacity and intermediation activity. Hence the relation between opacity, fragility and intermediation activity is an empirical question.

This thesis explicitly addresses this issue. Specifically, it exploits the theoretical literature on bank intermediation to develop concrete, testable hypotheses about the relations between bank fragility, opacity and intermediation. In order to test these hypotheses, measures of opacity, fragility and liquidity creation are required. However, this leads to an econometric challenge. Common measures of bank opacity that are available for the population of commercial banks rely on balance sheet information. The same holds true for the liquidity creation measures of Berger and Bouwman (2009). Because this latter measure is essentially a linear combination of various balance sheet categories, naïve regressions involving liquidity creation and opacity may well yield trivial results.

The empirical work carried out in Chapter 4 overcomes this challenge. This is accomplished by investigating a measure of bank intermediation quality, which is defined as the distance of a given bank from a stochastic liquidity creation frontier, obtained variously from SFA and GFA, spanned by the entire population of banks. This work exploits the fact that the GFA method is developed in Chapter 3, which allows for a validation of the SFA-based results. Such robustness checks are of substantial importance in this context because there is no established theory of liquidity efficiency and, hence, the traditional assumptions underlying the SFA approach may be violated. The results show strong support for the theory of Diamond and Rajan (2001), which advocates the view that both fragility and opacity are beneficial for bank intermediation. Hence Chapter 4 of this thesis contributes to the literature on banking and intermediation by showing that full bank disclosure may bring with it undesirable external effects in the form of impaired intermediation activity. Findings further highlight that it may be important to explicitly incorporate opacity into theoretical models of financial intermediation.

Up to this point, Chapter 3 investigates managerial ability in the context of value creation and shareholder value efficiency. In addition, Chapter 4 analyzes the influence that bank opacity and fragility have on the intermediation behavior of banks. It is therefore natural to further investigate whether any impact of managerial ability on intermediation obtains. This thesis hypothesizes that bank liquidity creation depends positively on the ability of managers. In addition, more able managers may be more confident in their own risk management skills and thus prone to taking greater risk. Neither of these hypotheses has as yet been tested empirically. While the prediction that more able managers will lead banks that are creating more liquidity is relatively intuitive in normal times, it is not clear whether managerial ability is conducive or detrimental to liquidity creation in crisis times. Thus it may be the case that the positive value implications of increasing liquidity market share during crises, documented by Berger and Bouwman (2008), will create incentives for managers to expand the intermediation activity of their banks during crises. Naturally, one would expect more able managers to better implement such a strategy. On the other hand, Bebchuk and Goldstein (2011) suggest that it may be individually rational for banks to curtail their intermediation activity during these periods. They show this in a setting in which the recovery rate on loans to industrial firms depends positively on the overall intermediation activity of the banking industry. Hence if some banks give few loans due to, for example, a negative signal about the state of the economy, it is individually rational for every other bank to also reduce its loan provisions. This results from the fact that any loans, which a given bank does end up extending, will suffer from the negative externalities emanating from the other banks' reluctance to lend. It is intuitive to suppose that more able managers will be better able to curtail their banks' intermediation activity rapidly if it is optimal to do so. Hence, on this reading, one would expect that managerial ability is negatively associated with liquidity creation during crises. Finally, it stands to reason that more able managers should be more effective at de-risking their banks in times of crisis. This conjecture is also as yet untested.

Therefore Chapter 5 addresses these open questions. Concretely, the chapter investigates the impact of managerial ability on liquidity creation and risk-taking both in normal times and during the recent financial crisis. Results, using Berger and Bouwman's (2009) liquidity creation measures, show that banks with more able managers create more liquidity during regular periods as hypothesized. Furthermore, in line with the initial conjecture, the results suggest that more able managers prefer to take more risk. In addition, a difference-in-differences approach reveals that the shock of the financial crisis reduces bank liquidity creation. More importantly, banks that are more ably managed reduce their liquidity creation more, which is in line with the prediction of Bebchuk and Goldstein (2011). Further examination shows that, to the extent that they are more able, bank managers also reduce the risk characteristics of their institutions during the crisis. This suggests that managers matter for the resilience of banks to shocks.

To sum up, this thesis extends the banking and efficiency literatures in a number of important ways. First, it develops and tests a novel efficiency parametrization method (generalized frontier analysis, GFA), which relaxes the assumptions of more traditional approaches. This new method can be exploited to study not only banks but also firms in other industries. Therefore it has the potential to be a valuable tool for future research in a variety of contexts. Second, this thesis offers an independent validation of the shareholder value efficiency concept by demonstrating its importance for the explanation of value creation in US banks and by showing that SHVE is more important than managerial ability in explaining bank value creation. Thus the present work offers a new method (GFA) and strengthens an existing concept (SHVE). Together this creates an opportunity for future research to resolve disparate findings in the banking literature regarding, for example, agency cost. Third, this thesis is the first to systematically investigate the interplay between bank intermediation, opacity and fragility. In so doing, it contributes to the understanding of the banking sector and allows for the deduction of meaningful policy implications. Specifically, results show that regulators would do well to allow for a certain degree of bank opacity so as not to negatively impact intermediation quality. Fourth, these results also highlight the need for a more explicit treatment of opacity in the theoretical literature and thus provide a meaningful direction for future work. Fifth, this thesis demonstrates that managerial ability is an important feature of banks and that this feature is systematically related to banks' liquidity creation and risk-taking. Importantly, the present results highlight that the information content of managerial ability varies between crisis times and normal times. Thus the present work provides an additional important insight into the functioning of banks and the banking sector. Finally, this insight suggests that policy makers may wish to consider managerial ability as an indicator variable when deciding not only on prudential but also on monetary policy.

This overview briefly motivates the issues addressed by the empirical chapters of this thesis and summarizes its main contributions. The emphasis in the empirical chapters (Chapters 3-5) is on a concise presentation of the main findings and each of these chapters is intended to be treated as a largely self-contained unit. Due to the difference in the questions being addressed, each of the chapters provides its own discussion of the relevant literature without creating redundancies. Furthermore, each chapter is accompanied by an appendix (Appendices A-C correspond to Chapters 3-5). These appendices present material and, where appropriate, also additional discussion that complements, supports and extends the findings reported in the empirical chapters but is not immediately required for the unfolding of the main arguments and hypothesis tests. The underlying theme of all chapters of this thesis is the efficiency of banks and the thesis contributes to the methodology of efficiency measurement in Chapter 3. Therefore, in order to put this work into perspective, Chapter 2 provides a discussion of conventional efficiency measurement methods, attendant data requirements and data gathering procedures employed in this thesis. Any empirical research is subject to a host of limitations. While each empirical chapter includes a number of robustness checks, room for possible extensions remains. These limitations and possible extensions are discussed in Chapter 6. Finally, Chapter 7 summarizes the main results and concludes.

2. Methods of Efficiency Measurement

This section provides the technical details that underpin the efficiency measurement methods most commonly encountered in the literature. These methods will be discussed in Section 2.1. Extensions to these standard methods as well as the remaining challenges of these approaches are addressed in Section 2.2. Finally, Section 2.3 discusses the data that is required for efficiency measurement and, in particular, the data that is used in the empirical chapters of this thesis.

2.1. Standard Efficiency Measurement Approaches

The two main approaches used for the parametrization of efficient frontiers are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Section 2.1.1 discusses DEA and Section 2.1.2 provides a basic description of SFA. While DEA has the advantage of being data-driven, noise substantially confounds efficiency estimates from this method. SFA, on the other hand, disentangles noise from signal but does so at the price of restrictive assumptions about the data generating process and the distribution of error terms.

2.1.1. Data Envelopment Analysis

Data envelopment analysis has the advantage of being non-parametric. This implies that a production function for the industry under investigation need not be specified a priori. The method relies on one or several linear programming problems. As there are very efficient algorithms available for the solution of such problems, the computational requirements of this method are moderate. However, the major disadvantage of DEA is that the efficient frontier that it generates is not able to account for statistical noise such as measurement or variable selection errors. This means that, if such errors exist in the data, they will drive the results in the sense that the noise will be subsumed into the efficiency scores. Furthermore, if certain regions of the sample space are only sparsely populated, DEA exhibits a strong bias towards classifying firms in those regions as being fully efficient. This has the potential to impair the validity and reliability of the resulting efficiency scores.

The DEA method is commonly attributed to Farrell (1957) although the term data envelopment analysis was coined only later. What follows is a very brief exposition of DEA, with notation and exposition in this entire section largely following Coelli, Rao, O'Donnell and Battese (2005), where a much more detailed discussion of this approach can be found. The discussion begins with technical efficiency, which then allows a simple extension to economic measures of efficiency such as cost, revenue and profit efficiency.

The basic idea of the method is to use cross-sectional firm-level data on inputs and outputs to map the I firms in the sample to the space spanned by their bundles of M inputs and N outputs. The individual firm i is assumed to maximize its efficiency, defined as the ratio between the total quantities of output ($\mathbf{y'}_i\mathbf{u}$) and input ($\mathbf{x'}_i\mathbf{v}$). This is achieved by choosing optimal weights ($\mathbf{u},\ \mathbf{v}$) for given combinations of input and output quantities, $\mathbf{x}_i$, $\mathbf{y}_i$. Here $\mathbf{x}_i$ and $\mathbf{y}_i$ are $M \times 1$ respectively $N \times 1$ vectors. To ensure uniqueness, the optimization problem is constrained by normalizing inputs for all firms to unity, i.e. $\mathbf{x'}_i\mathbf{v} = 1$. Furthermore, there are I constraints, one for each firm, which require that efficiency must not exceed unity for any one firm. The resulting linear program has the following form:

$$\begin{aligned} & \max_{\mathbf{u},\mathbf{v}} (\mathbf{y'}_i\mathbf{u}) \\ s.t.\quad & \mathbf{x'}_i\mathbf{v} = 1, \\ & \mathbf{y'}_j\mathbf{u} - \mathbf{x'}_j\mathbf{v} \leq 0 \quad j = 1, 2, ..., I, \\ & \mathbf{u}, \mathbf{v} \geq 0. \end{aligned} \tag{2.1}$$

Given the fact that I is the number of firms in the sample, the number of constraints $(I + 1)$ can be high and make computation relatively expensive. Therefore, in general, one will prefer to solve the dual problem. This is obtained by introducing a set of $I + 1$ dual variables $\boldsymbol{\lambda}$ and θ. Next, one transposes the constraint coefficient matrix and exchanges the right hand sides and the coefficients in the objective function. The constraints reverse direction and the problem becomes a minimization problem (if it was a maximization before).

$$\begin{aligned} & \min_{\theta,\boldsymbol{\lambda}} \theta \\ s.t.\quad & \theta\mathbf{x}_i - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & -\mathbf{y}_i + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \lambda \geq 0. \end{aligned} \tag{2.2}$$

In the objective function θ takes its unit coefficient from the 1st constraint above, while the I elements of the vector $\boldsymbol{\lambda}$ have zero coefficients from the I last constraints. $\mathbf{Y}$ and $\mathbf{X}$ are $N \times I$, respectively $M \times I$ matrices.

The problem aims at minimizing θ, which can be interpreted as the distance of any given firm from the efficient frontier following a ray emerging outward from the origin. This amounts to a radial contraction of the input vector which, however, cannot be so large as to lead to a departure from the feasible set spanned by the other firms in the sample. Consider a toy example in Table 2.1.

Table 2.1.: DEA Toy Example.

The first column labels firms, Column 2 gives the output quantity, Columns 3 and 4 provide the input quantities, while the last three columns hold the computed efficiency scores and the relative input quantities.

Firm	Output y	Input x_1	Input x_2	Efficiency Score	$\frac{x_1}{y}$	$\frac{x_2}{y}$
A	4.000	2.500	8.000	0.800	0.625	2.000
B	2.000	2.000	3.000	0.700	1.000	1.500
C	3.000	4.000	4.000	0.700	1.333	1.333
D	2.000	3.000	2.000	0.824	1.500	1.00
E	3.000	5.000	2.000	1.000	1.667	0.667
F	4.000	2.000	5.000	1.000	0.500	1.250
G	4.000	3.000	6.000	0.778	0.750	1.500
H	4.000	3.000	4.000	1.000	0.750	1.000
I	3.000	3.000	4.000	0.750	1.000	1.333

Given the data on inputs and outputs in Columns 2-4, one can compute the efficiency scores and relative input quantities in Columns 5-7. To visualize the results, consider Figure 2.1. Here the resulting frontier is defined by the firms with efficiency scores of unity (yellow circles) and is plotted in blue. Inefficient firms are plotted as black squares.

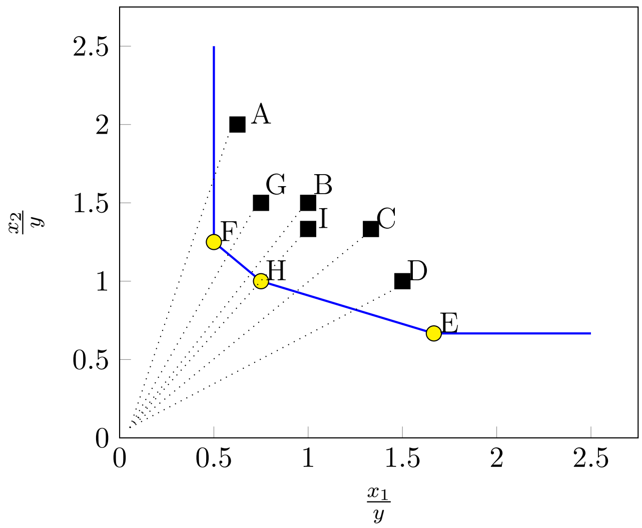

Figure 2.1.: Plot of Toy Example Efficient Frontier.

Input quantities scaled by the output quantity are plotted on the x- and y-axes. They relate to a two-input single-output technology. The blue, piecewise smooth curve is the frontier. Firms that are fully efficient are plotted as yellow circles, inefficient firms are plotted as black squares. Rays from the origin provide a graphical indication of the firms' inefficiency. The efficiency score can be visualized as the distance from the firm to the frontier along the ray divided by the total length of the ray.

Each firm's efficiency score will give the scalar by which one would need to multiply the input vectors for the respective firms in order to reach the frontier. For example, firm I could produce the same output with only 75% of the inputs it currently utilizes. The group of efficient firms that define each piece of the frontier constitutes the "peers" of that firm whose ray from the origin passes through the segment of the frontier defined by the peers. In Figure 2.1, E and H would form one group of peers (for C, D, and I). Firm H also forms a peer group with F (for B and G), while F is the only peer for firm A. Given these results, one can define technical efficiency as the quotient between the radial distance from the origin to the frontier and the distance from the origin to the actual point of production. In the present example it is justified to call the resulting point efficient for firms E, F and H.

In focusing on the reduction of inputs for a given level of outputs, the DEA model discussed so far has input orientation. The structure of an equivalent output oriented model is quite similar and therefore not discussed separately. The main difference is that, in the output oriented case, one obtains a piecewise smooth production possibility curve, rather than an isoquant. Under a constant returns to scale technology it is reasonable to expect identical efficiency scores for both models, while this does in general not hold in the variable returns to scale case. The set of firms labelled as efficient, however, remains constant for both in- and output orientation. This thesis follows the input oriented approach.

An important extension of this productive, or technical, efficiency is the case of economic efficiencies such as cost, revenue, and profit efficiency. As an example consider cost efficiency. In this type of model the firm is choosing the optimal input vector $\mathbf{x}_i^*$ so as to minimize total cost $\mathbf{w}_i{}'\mathbf{x}_i^*$ given input prices $\mathbf{w}_i$, while maintaining feasibility of the output $\mathbf{y}_i$. The constraints imposed on this model are again defined by the production possibilities set spanned by all other firms' in and outputs. Specifically, the problem can be expressed as follows

$$\begin{array}{ll} & \min_{\mathbf{x}_i^*,\boldsymbol{\lambda}} \mathbf{w}_i'\mathbf{x}_i^* \\ s.t. & -\mathbf{y}_i + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \mathbf{x}_i^* - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \mathbf{I1}'\boldsymbol{\lambda} = 1, \\ & \lambda \geq 0. \end{array} \tag{2.3}$$

Here, $\mathbf{I1}$ is an $I \times 1$ vector of ones and guarantees variable returns to scale as part of the convexity constraint. One defines total cost efficiency as the quotient between the cost incurred when cost-optimal inputs ($\mathbf{x}_i^*$) are chosen and the cost for the actually observed choice of inputs:

$$CE = \frac{\mathbf{w}_i'\mathbf{x}_i^*}{\mathbf{w}_i'\mathbf{x}_i}. \tag{2.4}$$

This approach is then easily extended to revenue and profit efficiency by either maximizing revenue through choosing optimal combinations of outputs, respectively by maximizing profit through choosing inputs and outputs simultaneously.

As noted at the outset, the main objection raised against DEA in the literature is the fact that this method cannot incorporate noise and measurement error naturally. Also, the scores obtained from such an analysis are strongly dependent on the sample of firms under observation. This makes DEA quite susceptible to sample selection problems. Nonetheless, DEA is one of the most commonly used methods in efficiency measurement due to its long history, easy implementation and low complexity.

2.1.2. Stochastic Frontier Analysis

The second main method currently used for frontier estimation in the literature is stochastic frontier analysis. See Berger and DeYoung (1997) for a survey and Kumbhakar and Lovell (2003), whom I follow in the below exposition, for a comprehensive treatment of the subject matter. As opposed to DEA, this method is computationally somewhat more costly. The main advantage that SFA exhibits over DEA is that it can accommodate statistical noise, such as for example measurement errors, in its specification of the frontier. However, this comes at the cost of having to specify a closed form for the data generating process and the distribution of the error terms ex ante.

After an adequate production function has been chosen to model the industry under consideration this can be used to specify the frontier stochastically like:

$$\ln y_i = \mathbf{x}_i'\boldsymbol{\beta} - u_i + v_i. \tag{2.5}$$

This representation assumes some log-linear production function. Here y_i represents the ith firm's output while $\mathbf{x}_i$ contains the K log inputs and $\boldsymbol{\beta}$ holds the unknown parameters. u_i and v_i are uncorrelated random variables associated with efficiency and statistical noise respectively. While v_i follows the customary assumptions (zero mean, homoscedasticity, no serial correlation) u_i is assumed to have a nonnegative mean in order to reflect that on average firms are not fully efficient. The most common specific assumptions are for v_i to be normally distributed, i.e. $v_i \sim iidN(0, \sigma_v^2)$, and for u_i to follow a truncated normal distribution, for example $u_i \sim iidN^+(0, \sigma_u^2)$. These assumptions are also followed in this thesis. Figure 2.2, adapted from Coelli, Rao, O'Donnell and Battese (2005) p. 244, illustrates the general features of such a frontier. Specifically, the frontier will vary about the deterministic component $\exp(\mathbf{x}_i'\boldsymbol{\beta})$, however it will itself be stochastic due to the presence of v_i so that the upper bound for the output values, also known as frontier output, is given by $\exp(\mathbf{x}_i'\boldsymbol{\beta} + v_i)$. The variation is explained by the two stochastic terms u_i and v_i, the inefficiency effect, and the noise effect respectively.

Figure 2.2 considers the case of a firm with only one input and one output. The frontier output is that output which one would expect to observe absent any inefficiency. The example $(-u_i < 0, v_i > 0)$ is arbitrary and merely chosen for illustration.

Once the model parameters have been estimated, it is possible to predict the inefficiency effect (or in other words technical inefficiency) like:

$$TE_i = \frac{y_i}{\exp(\mathbf{x}_i'\boldsymbol{\beta} + v_i)} = \exp(-u_i) \tag{2.6}$$

For reasons of computational efficiency this thesis implements a custom version of the steps needed to minimize the negative log-likelihood function in an SFA problem

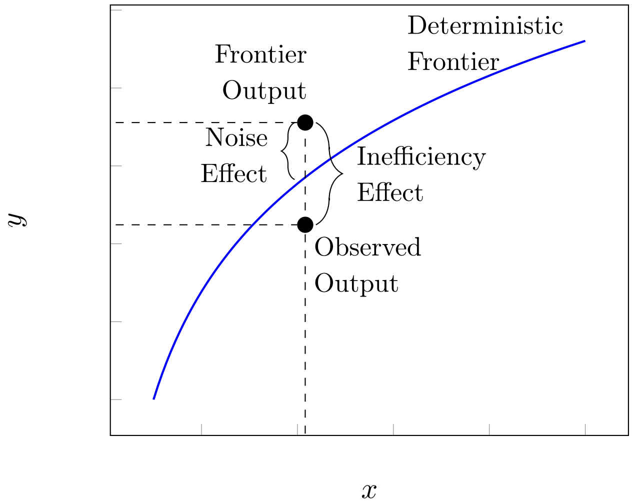

Figure 2.2.: Stochastic Frontier, Noise and Inefficiency Adapted from (Coelli, Rao, O'Donnell and Battese, 2005), p. 244.

Input quantities are plotted on the x-axis, while the y-axis displays output quantities of a single-input single-output technology. The blue curve represents the deterministic frontier. The black circles represent firm observations, which can come to lie above or below the deterministic frontier according to the relation between the noise and inefficiency effects.

in MATLAB®. The built-in function `fmincon` is used for the optimization. The calibration of this implementation was tested on the "Rice" data supplied by Coelli, Rao, O'Donnell and Battese (2005) and found to align exactly (to at least 5 decimals) with the results given in the tables in that work. To implement a problem like this, one must obtain the maximum likelihood function and, especially in cases with large samples, also analytical gradients. Following the derivation in Aigner, Lovell and Schmidt (1977), this can be achieved as follows:

Starting from the marginal distribution of the composite error $\epsilon = -u + v$

$$f(\epsilon) = \frac{2}{\sigma}\phi(\frac{\epsilon}{\sigma})[1 - \Phi(\frac{\epsilon\lambda}{\sigma})], \tag{2.7}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2, \lambda = \frac{\sigma_u}{\sigma_v}$ and ϕ and Φ represent the standard normal PDF and CDF respectively. One can then obtain the log-likelihood function for the normal-half normal stochastic frontier model. From

$$L(\mathbf{y}|\boldsymbol{\beta}, \lambda, \sigma^2) = \prod_{i=1}^{I} \frac{2}{\sigma} \frac{1}{\sqrt{2\pi}} \exp(-\frac{\epsilon_i^2}{\sigma^2})[1 - \Phi(\frac{\epsilon_i\lambda}{\sigma})] \tag{2.8}$$

where $i = 1, \ldots, I$ indexes observations it follows that

$$\ln(L(\mathbf{y}|\boldsymbol{\beta}, \lambda, \sigma^2)) = I \ln(\sqrt{(2/\pi)}) + I \ln(\frac{1}{\sigma}) + \sum_{i=1}^{I} \ln(1 - \Phi(\frac{\epsilon_i \lambda}{\sigma})) - \frac{1}{2\sigma^2} \sum_{i=1}^{I} \epsilon_i^2. \quad (2.9)$$

To maximize (or minimize the negative of) this function it is useful to use the partial derivatives with respect to the parameters. The required partials are given by:

$$\frac{\partial \ln(L)}{\partial \sigma^2} = -\frac{I}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^{I} \epsilon_i^2 + \frac{\lambda}{2\sigma^3} \sum_{i=1}^{I} \epsilon_i \frac{\phi(\frac{\epsilon_i \lambda}{\sigma})}{1 - \Phi(\frac{\epsilon_i \lambda}{\sigma})}, \quad (2.10)$$

$$\frac{\partial \ln(L)}{\partial \lambda} = -\frac{1}{\sigma} \sum_{i=1}^{I} \epsilon_i \frac{\phi(\frac{\epsilon_i \lambda}{\sigma})}{1 - \Phi(\frac{\epsilon_i \lambda}{\sigma})}, \quad (2.11)$$

$$\frac{\partial \ln(L)}{\partial \boldsymbol{\beta}} = \frac{1}{\sigma^2} \sum_{i=1}^{I} \epsilon_i \mathbf{x}_i + \frac{\lambda}{\sigma} \sum_{i=1}^{I} \mathbf{x}_i \frac{\phi(\frac{\epsilon_i \lambda}{\sigma})}{1 - \Phi(\frac{\epsilon_i \lambda}{\sigma})}, \quad (2.12)$$

where $\epsilon_i = (y_i - \boldsymbol{\beta}' \mathbf{x}_i)$ is the prediction error made for the ith firm using the log-linearized production function represented by the coefficients $\boldsymbol{\beta}$ with inputs $\mathbf{x}_i$.

Once the estimation has been completed, one needs to compute the firm-specific inefficiencies. This is done by using the traditional decompositions from the literature proposed either by Jondrow, Lovell, Materov and Schmidt (1982) or Battese and Coelli (1988). Letting $\mu^* = -\frac{\epsilon \sigma_u^2}{\sigma^2}$ and $\sigma^* = \frac{\sigma_u^2 \sigma_v^2}{\sigma^2}$, the Jondrow, Lovell, Materov and Schmidt estimator can be expressed as

$$E[u_i|\epsilon_i] = \mu_i^* + \sigma^* \left[\frac{\phi(-\frac{\mu_i^*}{\sigma^*})}{1 - \Phi(\frac{-\mu_i^*}{\sigma*})} \right] \quad (2.13)$$

and gives the point estimate $TE_i = \exp\{-E[u_i|\epsilon_i]\}$. The Battese and Coelli estimator can be written as

$$TE_i = E[\exp\{-u_i\}|\epsilon_i] = \left[\frac{1 - \Phi(\sigma^* - \frac{\mu_i^*}{\sigma^*})}{1 - \Phi(\frac{\mu_i^*}{\sigma^*})} \right] \exp\{\mu_i^* + \frac{1}{2}\sigma^{*2}\}. \quad (2.14)$$

Kumbhakar and Lovell (2003) give support to the usage of the latter by arguing that the former "...includes only the first term in the power series expansion of $\exp\{-u\}$" (p. 77). Hence this thesis follows the latter approach.

This general approach to efficiency estimation can be applied to economic efficiency, such as for example cost efficiency, by carrying out some simple sign changes (most notably $\epsilon_i = u_i + v_i$ see for example Kumbhakar and Lovell (2003) pp. 75-77 and pp. 140-141). Furthermore, it can be made more specific by explicitly defining the deterministic frontier component. The general cost efficiency model then becomes

$$C_i = c(\mathbf{y}_i, \mathbf{w}_i, \boldsymbol{\beta}) \exp(\epsilon_i), \tag{2.15}$$

where $\mathbf{w}_i$ are input prices and $\mathbf{y}_i$ are output quantities. It is frequent in the literature to find the Translog parametrization of the efficient frontier and this thesis follows this tradition. The variable stochastic cost function of the Translog form is given by:

$$\begin{aligned}
\ln C_i = \beta_0 &+ \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \sum_{n=1}^{N} \beta_n \ln w_{ni} + \sum_{q=1}^{Q} \gamma_q \ln z_{qi} \\
&+ \frac{1}{2}\sum_{m=1}^{M}\sum_{j=1}^{M} \alpha_{mj} \ln y_{mi} \ln y_{ji} + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \beta_{nk} \ln w_{ni} \ln w_{ki} \\
&+ \frac{1}{2}\sum_{q=1}^{Q}\sum_{r=1}^{Q} \gamma_{qr} \ln z_{qi} \ln z_{ri} + \sum_{m=1}^{M}\sum_{n=1}^{N} \delta_{mn} \ln w_{ni} \ln y_{mi} \\
&+ \sum_{m=1}^{M}\sum_{q=1}^{Q} \eta_{mq} \ln y_{mi} \ln z_{qi} + \sum_{q=1}^{Q}\sum_{n=1}^{N} \kappa_{qn} \ln w_{ni} \ln z_{qi} + u_i + v_i.
\end{aligned} \tag{2.16}$$

Here y_{mi} represents the quantity of output m produced by firm i, w_{ni} represents the price of the nth input used by firm i and z_{qi} is the quantity of the qth fixed input used by the ith firm. $\alpha, \beta, \gamma, \delta, \eta$ and κ are coefficients to be estimated. In other words, one specifies the cost function in terms of the output quantities and input prices under the assumption that input quantities are chosen so as to minimize cost. Linear homogeneity in prices requires that one impose the following restrictions:

$$\sum_{n=1}^{N} \beta_n = 1 \tag{2.17}$$

$$\sum_{n=1}^{N} \beta_{nk} = 0 \ \forall k \tag{2.18}$$

$$\sum_{n=1}^{N} \delta_{nm} = 0 \ \forall m \tag{2.19}$$

$$\sum_{n=1}^{N} \kappa_{nq} = 0 \ \forall q. \tag{2.20}$$

The usual symmetry conditions are $\alpha_{mj} = \alpha_{jm}, \beta_{nk} = \beta_{kn}, \gamma_{qr} = \gamma_{rq}$.

For the parametrization of revenue and profit frontiers a similar approach can be taken. In the case of profit functions the result is the so-called alternative profit function approach of Berger and DeYoung (1997) and is particularly appropriate when services offered by firms differ in terms of their quality, outputs are not freely disposable, there exists some degree of market power or there is noise in the measurement of output prices. It is likely that one or all of these conditions are met in the banking industry. Hence, in so far as it deals with efficiencies other than cost or revenue efficiency, this thesis adopts this alternative approach.

The main advantage of the SFA method is its stochastic nature, which allows it to distinguish between signal and noise. However, this capability comes at the cost of possibly restrictive assumptions about the functional form of the production technology and the distribution of the error terms. Hence the literature has suggested extensions to this method, which will be discussed Section 2.2.

2.2. Alternative Efficiency Measurement Approaches

This section deals with extensions of the standard efficiency measurement methods as well as with alternative approaches to efficiency measurement. Specifically, Section 2.2.1 discusses some extensions to the standard DEA and SFA methods. This discussion highlights some of the problematic aspects of these standard approaches and shows that even the available extensions cannot fully resolve these concerns. Furthermore, Section 2.2.2 provides a summary of the literature, which proposes to utilize artificial neural networks for the task of efficiency measurement. This discussion shows that, although promising, the present efforts in this direction create challenges of their own. Taken together, this discussion motivates the development of the GFA method in Chapter 3.

2.2.1. Extensions of the Standard Approaches

Since DEA suffers most from its deterministic nature, it is not surprising that efforts have been made to relax this constraint. Consider for example Kao and Liu (2004) and Kao and Liu (2009). The former study uses interval-based bank-internal projections for in and outputs to produce forward-looking forecasts. The heuristic approach of the latter study makes the assumption of beta distributed in and outputs and estimates the parameters from the data. Then a Monte-Carlo exercise is used to obtain distributions for the efficiency measures calculated by way of DEA. Critically, these studies do not address the DEA method itself but rather modify the data used to obtain the DEA estimates so as to reflect some random influences. In contrast, Simar and Wilson (1998), Simar and Wilson (2000) and Kneip, Simar and Wilson (2008) propose methods for obtaining bootstrap estimates for DEA efficiency scores. In particular, they resolve problems of inconsistency that follow from the application of a naïve bootstrap. However, their use of smoothing requires arbitrary choices of parameters such as bandwidth. Decision choices such as these are ultimately left at the discretion of the researcher. In addition, notwithstanding the efficiency of available solvers for linear programming problems, this method is computationally extremely costly due to the large number of linear programs that need to be evaluated. Finally, Post, Cherchye and Kuosmanen (2002) and Post (2007) present an approach that attempts to compute efficiency locally by searching for nearest neighbors to any given firm in neighborhoods of decreasing size. However, while computationally efficient, this method requires the appropriate choice of distance measure between firms for which no guidance exists in the literature. Moreover, their method is restricted to providing an ordinal efficiency estimate relative to the sample mean, which may or may not be sufficiently informative depending on the context of the investigation.

Important extensions of the SFA approach include the parametrization of panel data models provided by Battese and Coelli (1992) and Battese and Coelli (1995). However, although important, these advances do not suffice to alleviate the main concern about the SFA method. This concern relates to the functional form assumption. The commonly used Translog functional form, for example, is based on a second order Taylor expansion and thus achieves only a local fit. This shortcoming motivates the alternative "Fourier Flexible" (henceforth FF) functional form (see for example Gallant, 1981, Gallant, 1982 and Akhigbe and McNulty, 2003). This approach uses a Translog function as a starting point and then adds an arbitrary number of orthogonal series terms (sines and cosines) to this function in order to increase its flexibility. Thus, for example, Mitchell and Onvural (1996) argue that because the Translog is nested within the FF as a special case, significantly different results from the two functions will allow one to test for any bias inherent in the Translog. They use the FF to investigate the existence of scale and scope economies in their sample of US banks for the years 1986 and 1990. The authors find that even for their homogeneous sample of medium to large banks the production function does not follow a Translog form and that the FF and Translog will lead to different conclusions as to the presence of scale and scope economies. However, a problem with the FF approach is that the number of trigonometric terms to be added to the specification is arbitrary. Mitchell and Onvural (1996) do propose a rule of thumb, which suggests that the number of terms should be approximately equal to the number of observations raised to the two-thirds power. However, such rules of thumb are obviously ad-hoc and subjective. In addition, this heuristic can lead to a proliferation of parameters in large samples, which may make the FF method susceptible to overfitting and computationally costly. Thus, computational challenges induce Mitchell and Onvural (1996) to drop the customary regularity conditions (concavity, monotonicity) that are normally assumed to hold for economic production functions. Feng and Serletis (2009) attempt to alleviate this issue by using nonlinear constrained optimization. Computational challenges prevent them from calculating standard errors, however. While they do relax this shortcoming in a later study, the computational costs remains sufficiently high to force them to split their sample into smaller subsamples and estimate separate frontiers (Feng and Serletis, 2010). This may be warranted in some industries and time periods but not in others. Thus computational complexity constitutes an inherent limitation of the FF approach.

Alternatives to the FF method are proposed by, for example, McAllister and McManus (1993) and Wheelock and Wilson (2001). McAllister and McManus (1993) argue that disparate findings about economies of scale in the banking industry are mainly due to misspecification of the frontier in terms of the functional form and choice of inputs. Hence, in addition to the FF approach, they also use semi-nonparametric methods such as Kernel Regression and Linear Splines. They find that the Translog function is misspecified for their broad sample of banks and that, out of the proposed alternatives, the linear spline approach provides the best estimates of scale efficiency. Wheelock and Wilson (2001) are also concerned about the applicability of the Translog function. Moreover, they stress the subjectivity involved in determining the number and type of orthogonal terms to include in a Fourier Flexible estimator. As an alternative they suggest the use of kernel regression and local polynomial smoothing. The authors argue that these alternative methods provide a theoretically better grounded model selection process than is available for the FF approach. Using their alternative techniques, they show that scale efficiencies obtained on the basis of the Translog functional form are unstable. Finally, the approach of Fan, Li and Weersink (1996) is a modification that aims at making SFA semi-parametric. The approach uses a kernel-regression estimator in the first stage and a parametric second stage estimation. Unfortunately these alternative methods also involve arbitrary parameter choices such as the smoothing bandwidth.

This discussion shows that the literature has recognized the need to relax the assumptions of the traditional methods. Moreover, this body of research has collated empirical evidence to suggest that the conventional assumptions are frequently not tenable. As alternatives it proposes approaches that address the original limitations. However, these alternative methods either entail ad-hoc assumptions of their own or cause excessive computational cost. Therefore the literature has also turned to artificial neural networks, a flexible class of general functional approximators, to find alternatives to the approaches discussed so far.

2.2.2. Existing Work on Efficiency Measurement with Artificial Neural Networks

This section provides a review of the extant literature concerning the use of artificial neural networks for firm level efficiency. This line of research has emerged only fairly recently, which is the reason why the existing body of literature is small compared to the large number of studies dealing with efficiency.[1] Therefore this thesis is able to provide a very comprehensive review of this literature.

Artificial neural networks (henceforth ANNs) are a flexible class of algorithms, which have been shown to be able to approximate functions and their quantiles to an arbitrary degree of accuracy (see for example Hornik, Stinchcombe and White, 1989, White, 1992). Since, Artificial neural networks have been used successfully in tasks as diverse as dimensionality reduction (Hinton and Salakhutdinov, 2006), pattern recognition (for example Graves and Schmidhuber, 2005 and Yang, Yu, Gong and Huang, 2009), language modeling (Bengio, Ducharme, Vincent and Jauvin, 2003) and time-series analysis (Zhang, 2007 and Crone and Kourentzes, 2010). They can perform well on many classification and pattern recognition tasks by combining multiple layers of connected, simple computational units. Each of these units carries out a summation of the signal it obtains from the preceding units to which it is connected. It then applies a, usually nonlinear, function to the resulting quantity and sends this signal to all subsequent units. The intensity with which units are connected to preceding and subsequent units can be modified so as to "train" the entire structure to separate signal from noise. This procedure is made more precise in Section 3.2.

ANNs have important advantages over both SFA and DEA. Specifically, they are both non-parametric and stochastic. In other words, they require neither assumptions about the distribution of errors, the functional form of the production technology nor about the precision with which the data are observed. However, their main disadvantage is that they do not readily provide efficiency scores. In their seminal study Athanassopou-

[1] As an indication of this consider the fact that survey studies which explicitly center around the application of techniques from Operations Research or Artificial Intelligence in Banking, such as for example Fethi and Pasiouras (2010), make no mention of this branch of the literature.

los and Curram (1996) suggest two possible approaches to obtain efficiency scores from ANNs. First, the efficiency score is simply defined as the ratio of observed output and the output predicted by the ANN, given the observed inputs. This approach, however, does not naturally prevent the resulting efficiency scores from exceeding unity, which is difficult to justify. Therefore their second approach, which they call "standardised efficiency", uses as denominator the predicted outputs plus the maximum of the prediction error across all observations. This latter approach can be interpreted as shifting the unknown efficient frontier outward.[2] Figure 2.3 illustrates this approach. Here the average production function is represented by the dashed line. It is then shifted outward to the full line by the largest observed error. This results in efficiency scores less than unity and makes ANNs, SFA and DEA comparable. Athanassopoulos and Curram (1996) test their approach on both simulated and observed data. Specifically, they generate artificial data following a piecewise two-factor Cobb-Douglas production function with varying returns to scale. The observations are then contaminated with noise and measurement errors following a variety of distributions. They also apply their method to a dataset of bank branches. In general, they find on artificial data that DEA gives lower deviations from the true known efficiency levels and thus outperforms the ANN approach. In the application to real world data the ANN classifies a larger number of firms as efficient based on the un-standardized measure of efficiency since it is fitting a nonlinear average production function to the data rather than searching for an envelope. This shows the main weaknesses of the approach advanced by Athanassopoulos and Curram (1996).

The first study to build on these results was that of Costa and Markellos (1997). They analyze the technical efficiency of the London Underground between 1970 and 1994. Their study uses both DEA and ANNs for efficiency measurement and, in particular, proposes two different types of ANN architecture to yield different kinds of efficiency estimates. One architecture with an "average" number of hidden units is intended to model the production technology, while the alternative ANN architecture has a very large number of units. It is well known that this type of structure will induce overfitting since increasing the number of units is tantamount to increasing the number of parameters. The authors argue that using this kind of ANN will generate efficiency estimates, which are closer to the DEA estimates. Specifically, they argue that an overfitted ANN will provide a hull for the data. This argument appears very problematic, however. Overfitting generally induces the algorithm in question to "learn" not only the

[2]Note that increasing the denominator of the quotient defining efficiency decreases its numerical value. Conversely, the frontier is thus shifted outward.

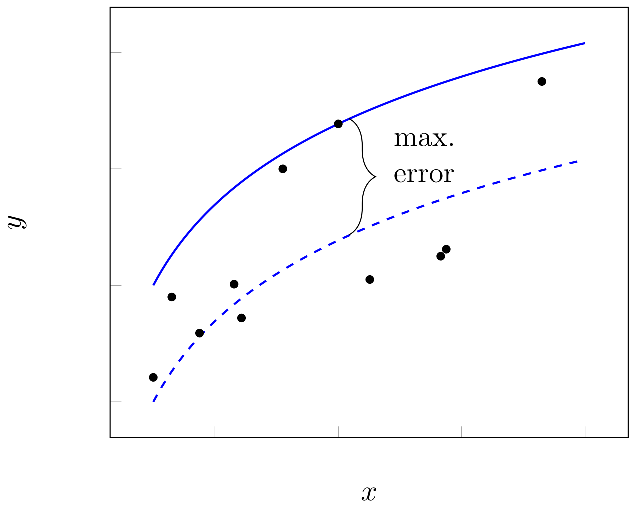

Figure 2.3.: Schematic Example of Frontier Shift.

Input quantities are plotted on the x-axis, while the y-axis displays output quantities of a single-input single-output technology. Black dots represent bank output observations. The dashed line represents the average production function, while the regular line symbolizes the frontier resulting from the shifting approach of Athanassopoulos and Curram (1996).

true patterns underlying the data generating process but also any noise that is included in the sample. This has the potential to severely impair performance on unseen data. Therefore there is no reason to believe that merely overfitting an ANN will yield an upper bound to the production possibility set.

Some studies construct an artificial production technology and assess the performance of ANNs on simulated data. This literature includes for example Guermat and Hadri (1999), Santín, Delgado and Valiño (2004), Santín (2008) and Emrouznejad and Shale (2009). Guermat and Hadri (1999) use a CES, generalized Leontief, Cobb-Douglas and Translog specification and they add two sources of error, one representing noise, the other inefficiency. They compare the accuracy of the predicted efficiency rankings obtained using the ANN with rankings resulting from an SFA approach. They find that the rankings produced by the ANN are more robust to noise, that increasing sample size has a positive influence on performance and that the CES and generalized Leontief functions are more difficult for the ANN to approximate. Santín, Delgado and Valiño (2004) compare the efficiency estimation performance of ANNs with the results obtained from ordinary least squares, corrected ordinary least squares, DEA and SFA. They evaluate the correlation between the estimated and true efficiency scores for each of the methods under examination. For their piecewise continuously differentiable production function, which shows increasing, decreasing and constant returns to scale in different segments, they find that the results generated by the ANN dominate the results obtained from other methods. Santín (2008) follows a similar approach and compares the results generated by an ANN with those of SFA and DEA. Concretely, he uses small datasets with 50 observations of simulated data. Noise and random inefficiency are injected and he implements a thick frontier modeling approach for the ANN. He defines a thick frontier by using the maximum error for subsets of observations in order to shift the average production function outward. Comparing the correlation of estimated and theoretical efficiencies, he finds that the ANN model outperforms all other models, with SFA providing the worst results. The study by Emrouznejad and Shale (2009) also uses synthetic data. However, their aim differs from preceding studies in that the authors attempt to investigate the ability of an ANN to approximate efficiency scores generated by a DEA model. The authors justify this counterintuitive approach by arguing that the computational cost incurred in DEA studies is large for very large samples. Given the efficient linear programming algorithms available for the solution of DEA problems, this motivation does not seem very compelling. They find a high ability of their ANN to approximate the frontier generated by DEA with low computational cost.

Some authors study the performance of ANNs on real data. These include the work of Wang (2003), who proposes an ANN as an alternative to DEA with the principal motivation of improving upon the deterministic nature of DEA. An interesting feature of his approach is that the results of a DEA analysis and an ANN are combined linearly to ultimately provide information about the frontier. The weight attributed to each of the results in the combination is determined by the distribution of the error terms obtained from the combination. He finds that, for noisy data, the ANN-DEA hybrid performs better than DEA alone. A minor expansion of the literature is provided by Delgado (2005), who argues that to construct a thick frontier not the largest error but an average of the largest 5% of errors should be used to induce the shift in the ANN frontier. In line with the literature he finds that ANNs perform well in his sample. Pendharkar and Rodger (2003), on the other hand, use DEA as a pre-processing technique and they train the ANN on data, which is clustered into homogeneous groups by efficiency. Again, they find strong results for the ANN. A similar result is found by Wu, Yang and Liang (2006) in their application of ANNs to the efficiency estimation of bank branches. They carry out ANN learning on subsets of the data grouped according to their DEA-efficiency scores. Azadeh, Ghaderi, Anvari, Saberi and Izadbakhsh (2007) propose a slightly different approach in that they develop an elaborate data pre-processing procedure based on Fuzzy-C-means clustering. Here the shift of the ANN-generated frontier is carried out for each efficiency-cluster in turn. Application to a small sample of Iranian power plants illustrates their method. This approach is applied with virtually no material changes by Azadeh, Saberi and Anvari (2010) and Azadeh, Saberi and Anvari (2011). The only difference is that Azadeh, Saberi and Anvari (2010) introduce a sensitivity analysis while Azadeh, Saberi and Anvari (2011) also apply the algorithm to a small sample of data concerning the global automobile industry.

Michaelides, Vouldis and Tsionas (2010) and Vouldis, Michaelides and Tsionas (2010) use ANNs in the context of efficiency estimation in a distinctly different way to the preceding literature. Specifically, they introduce the "neural distance function". This concept aims to use the ANN computational kernel for the estimation of output distance functions. This is especially beneficial in cases involving multi-output technologies. Concretely, the ANN computational kernel is used to approximate the reduced form equations in a Translog system, giving each output as a function of inputs only. In this respect the ANN can be said to partially model the production technology underlying the production of the firm. Ultimately though, the Translog form makes use of the outputs generated by the ANN. In their application of the ANN algorithm to the reduced form equations they find that the informationally most crisp, as well as the most frugal, specification includes only one unit. Given that a logistic function is used as activation function in the ANN's units, each reduced form equation boils down to a logistic regression, essentially making the ANN strategy unnecessary. Both studies apply their method to a large sample of US banks between the years 1989 and 2000. They check their method on artificial data generated by a Translog function for robustness and find very good results. While this approach does extend traditional SFA by introducing the ANN concept into the estimation, it is not the ANN that ends up estimating the efficiency scores.

The seminal work of Athanassopoulos and Curram (1996) is important in that it initiates the debate on neural networks and efficiency. In addition, although this is not explicitly stated, the authors recognize and address the need to provide both an estimation component (in their case the ANN) and a frontier component (in their case the shifting approach). These types of components are pervasive in all efficiency parametrization methods. Thus, for example, SFA uses maximum likelihood coupled with the parametric functional form as the estimation component and the assumption about the distribution of the error terms as the frontier component. DEA, on the other hand, uses linear programming as the estimation component, whereas the inherent convexity assumption provides the frontier component. The contribution of Athanassopoulos and Curram (1996) is to recognize the possibility of using ANNs for the estimation component. However, a weakness of their approach is the arbitrariness of the frontier component. Unfortunately, as the preceding discussion shows, the literature on ANNs in the context of efficiency has inherited this weakness. Hence, while promising, the ANN approach to efficiency measurement requires further work. This gap is filled by the generalized frontier analysis method, which is introduced in Chapter 3.

2.3. Data and Variable Selection in Efficiency Measurement

Any efficiency measurement approach must consider the empirical question of selecting variables that are reflective of the production process of the industry under investigation. Section 2.3.1 discusses a number of conceptual approaches to selecting inputs and outputs when measuring the efficiency of banks. Subsequently, Section 2.3.2 discusses the definition of economic value added for banks, which is an important variable used especially in Chapter 3. Finally, Section 2.3.3 discusses the data selection and filtering rules used in obtaining the data on which subsequent analyses are based.

2.3.1. Definition of Bank Inputs, Outputs and Prices

A number of approaches for the classification of bank inputs and outputs have been advanced in the literature. The value added approach, advocated by Berger and Humphrey (1992), uses operating cost to classify outputs as important and unimportant in terms of their value addition. Concretely, it considers the classification of assets and liabilities as inputs or outputs to be a question of degree and not fixed a priori. Rather, under this paradigm, the classification of assets and liabilities as financial inputs and outputs depends on their importance in driving bank expenses. Thus, empirically, one would regress expenses for physical inputs (labor and capital) on the asset and liability quantities. The magnitude of the coefficients on the asset and liability classes in question will then provide an indication of the importance of each asset and liability class and thus yield the value added classification. Less common but similar is the user cost approach, which stipulates that whether an asset or a liability is an input or an output should be determined endogenously by considering whether the marginal revenue exceeds the user cost of capital (Hancock, 1985). It differs from the value added approach in that it treats operating cost as implicitly determined by the profit maximization of the bank rather than as explicitly parametrized. While the opportunity cost argument underlying this approach is sound, empirical difficulties arise. These mainly stem from noisy estimates of marginal cost and marginal revenue required to partition assets and liabilities into inputs and outputs, as well as from a high sensitivity of results to the underlying assumptions and data such as interest rates (Berger and Humphrey, 1992). The competing production approach, on the other hand, is deemed more important in assessing the performance of individual bank branches. This is because it focuses on the quantity of services provided such as, for example, the number of accounts serviced, rather than the volume of monetary transactions (Berger and Humphrey, 1997). Because this thesis focusses on banks as intermediaries, this approach is less important in the present context.

A major shortcoming of these approaches is that off-balance-sheet items and securities tend to be ignored, primarily because of the difficulty of obtaining reliable revenue data on these assets. However, the modern banking landscape relies on such instruments for the provision of trade credit, guarantees and hedging of risks. In addition, with the exception of the value added approach, all the approaches mentioned above are relatively rarely encountered in the empirical banking literature which makes comparability of new results with prior findings difficult. In general, a large number of studies seem to adopt the intermediation, also known as the asset, approach propounded by Sealey and Lindley (1977) in order to define in- and outputs.[3] This approach, discussed below in greater detail, focuses on the functional role of banks as intermediaries in the wider economy. Hence it aligns well with the context of this thesis and is therefore followed in the remainder of the investigation. Overall, possibly with the exception of the production approach, the intermediation, value added and user cost approaches tend to overlap substantially in terms of the input and output classes they consider.[4] This suggests that the choice of classification approach may not be as critical empirically as it appears to be conceptually.

Within the intermediation approach there is broad consensus that labor, physical capital and financial capital should constitute the inputs. In addition, some studies include equity capital as a fixed input (see for example McAllister and McManus, 1993 and Akhigbe and McNulty, 2003). This thesis defines labor, purchased funds and core deposits as variable inputs, while equity capital and fixed assets are considered fixed. Equity is fixed in the short run at least and also has a limited scope for variation.

[3] This notion is confirmed by surveys such as Berger and DeYoung (1997) and Fethi and Pasiouras (2010).

[4] As an example see the subsequent discussion of the intermediation approach and compare this with Hancock (1985), who uses the user cost approach and finds that outputs are demand deposits and all loans and inputs are labor, physical capital, cash, time deposits and capital, which is held fixed. Furthermore, Berger and Humphrey (1992) find that the value added approach tends to classify as outputs all loans (consumer-, real estate-, and commercial) and demand and time and savings deposits. This latter category is assigned a dual input and output role however. Inputs are mainly purchased funds, labor and physical capital. Government securities and other nonloan investments are deemed unimportant outputs.

Capitalization that is too low will cause intervention from the regulator. Capitalization that is too high will lead to a firm that is not in fact an intermediary. Thus it appears justified to treat equity capital as fixed. Fixed assets are also not likely to be freely disposable in the short run. Acquisitions or divestitures of substantial portions of the premises and other fixed assets are usually one-off strategic decisions that are not routinely modified.

In terms of outputs the literature includes various classes of loans as well as securities (see for example Altunbas and Chakravarty, 2001 and Asaftei, 2008). In addition, off-balance-sheet items constitute a component of bank output with increasing importance. Therefore this thesis considers loans, subdivided into commercial, real estate and consumer loans and securities as variable outputs. Off-balance-sheet items are considered as fixed outputs. The main reason for this attribution is the fact that many off-balance-sheet item classes have no direct income other than fee income (such as letters of credit) while certain off-balance-sheet items, such as derivatives, often serve purposes other than income generation. Moreover, the available data do not afford access to the income generated from this class of assets. Thus a calculation of the output price is not possible without introducing a substantial degree of subjectivity by arbitrarily defining income from off-balance-sheet items. To avoid this subjectivity I prefer to err on the side of caution and define this asset class as fixed. Overall, the selection of inputs and outputs follows Berger, Bonime, Goldberg and White (2004) and Berger and Mester (2003). Table 2.2 summarizes the input and output classes along with the appropriate price definitions.

The subsequent empirical applications will consider economic efficiencies. These require the availability of in and output prices for their parametrization. This is often accomplished in the literature by dividing flows by stocks. Thus the price of labor can, for example, be determined from the total wage expense divided by the number of employees (Berger and DeYoung, 1997). However, prices estimated in this way can be prone to outliers. Therefore this thesis follows Berger and Bonaccorsi di Patti (2006). These authors calculate average faced market prices by first computing the price of each bank as discussed above. They then investigate individual geographical markets. Specifically, they consider each metropolitan statistical area (MSA) respectively each county that is not an MSA. In such a regional market a reasonable approximation to the market price is the average price of all banks operative there. The weight of each bank in the market is set as the market share of the respective bank in terms of deposits.[5] Furthermore, since each individual bank is assumed to be a price taker in each of its

[5] I obtain data on deposits from the Federal Deposit Insurance Corporation (2012).

Table 2.2.: Definition of Inputs, Outputs and Prices for Efficiency Estimation.

Inputs	**Input Prices**	**Outputs**	**Output Prices**
Labor (Number of full-time equivalent employees)	Total personnel expenses/ labor	Consumer loans	Interest income from consumer loans/ consumer loans
Purchased funds	Cost of purchased funds/purchased funds	Business loans	Interest income from business loans/ business loans
Core deposits	Cost of core deposits/core deposits	Real estate loans	Interest income from real estate loans/real estate loans
Equity capital	*Fixed input*	Securities (Non-loan-, non-fixed-assets)	Total non-loan, interest income/securities
Fixed assets	*Fixed input*	Off-balance-sheet items	*Fixed output*

markets, only all the other banks are taken into account when computing a given bank's market price. Globally, the price that is relevant for each bank is then defined as the price it faces in each of its markets weighted by the share of deposits that it maintains in these markets in terms of its total deposits. More formally, assuming one of n banks active in market j, bank i, has deposits $d_{i,j}$ in that market, which is one of m markets which the bank services, then that market's importance for the bank is computed as:

$$w_{i,j} = \frac{d_{i,j}}{\sum\limits_{j=1}^{m} d_{i,j}}. \tag{2.21}$$

Also let each bank's raw price, computed from the balance sheet data as in Table 2.2, be $p^r_{i,j}$. Then, if the bank is assumed to be a price taker, the price, $p_{i,j}$, faced by bank i in market j, can be expressed as:

$$p_{i,j} = \sum_{k=1,k\neq i}^{n} \left(\frac{d_{k,j}}{\sum\limits_{l=1,l\neq i}^{n} d_{l,j}} p^r_{k,j} \right). \tag{2.22}$$

Consistent with the assumption of price taking behavior, this price depends only on the raw prices of the other banks active in the respective market, $p^r_{k,j}$. Then the price which the bank faces globally, taking into account all m markets it services, can be computed as:

$$p_i = \sum_{j=1}^{m} w_{i,j} p_{i,j}. \tag{2.23}$$

Prices computed in this way are less noisy, conform to economically plausible behavioral assumptions and are less driven by outliers for individual banks.

2.3.2. Computation of Economic Value Added

This thesis is the first to investigate the shareholder value efficiency of US banks. The shareholder value efficiency concept was introduced by Fiordelisi (2007) and is discussed in greater detail in Chapter 3. I follow this author in defining the required measure of value creation. In particular, this thesis proxies value creation by economic value added (EVA). A measure like EVA is particularly useful for two reasons. First, for example Rogerson (1997) has shown that a residual income measure of the EVA type can be used by firm owners to formulate remuneration contracts which induce efficient investment decisions on the part of managers. Second, EVA depends on relatively frugal data requirements and can, with only modest assumptions, be applied to datasets such as the present one, where a majority of banks are not listed on a stock exchange. The economic value added generated between period $t-1$ and t can be defined as follows:

$$EVA_{t-1,t} = EP_{t-1,t} - \kappa C_{t-1}, \tag{2.24}$$

where $EP_{t-1,t}$ is the economic profit (net operating profit after tax between period $t-1$ and t), κ is the cost of capital and C_{t-1} is the capital invested by the bank during the preceding period. Table 2.3 gives an overview of my specification for economic profits and capital invested. In computing EVA, this thesis follows the design of Fiordelisi (2007) and Fiordelisi and Molyneux (2007) in spirit. However, some adjustments are necessary because of substantial differences between US-GAAP and IFRS/IAS and data availability (Call Reports vs Bankscope). When computing the economic profit, also referred to as net operating profit after tax (NOPAT) in the EVA literature, several adjustments are made to reflect the economic realities of the bank (for a detailed discussion see for example Uyemura, Kantor and Pettit, 1996). Specifically, the economic profit should only take into account cash taxes paid and exclude deferred tax provisions because these are de facto funding sources due to their often permanent nature. However, the Call Report does not allow access to the deferred portion of applicable income

Table 2.3.: Definition of the Components of EVA.

	Economic Profit
	Net income/loss attributable to bank
+	Other noninterest expense
+	Provision for loan and lease losses
−	Net charge-offs on the above
+	Provision for allocated transfer risk reserve
−	Net charge-offs on the above
	Capital invested
	Total bank equity capital (book value)
+	5-year moving sum of other noninterest expense
−	5-year moving average of other noninterest expense
+	Net loan-loss reserve
+	Transfer risk reserve

taxes. One possibility would be to start with pre-tax income in calculating economic profits. However, this would overstate the actual income generated. In addition, all banks are subject to the same federal tax. Hence the cross sectional distortion caused by the unavailability of the deferred tax position is unlikely to be material since the only difference between banks will be caused by state taxes, which usually do not exceed 15% (The Tax Foundation, 2012). Therefore omitting taxes in the computation is unlikely to bias inference. For this reason and so as to err on the side of caution in terms of the reported value created by banks, this thesis uses net income/loss after tax as the starting point for economic profits. Moreover, it is appropriate to adjust the economic profit by non-recurring events. These could, for example, be R&D expenses or training expenses. In addition, operating lease expenses are related to financing rather than the core intermediation business of the bank (Uyemura, Kantor and Pettit, 1996). Such expenses are captured in the other noninterest expense position and hence added back to the net income of the bank. The main adjustment applicable to bank income statements when computing EVA is related to loan and lease loss provisions. The provisions themselves tend to be used to smooth earnings and thus confound the economic reality of the bank. Instead, Uyemura, Kantor and Pettit (1996) argue that it may be more appropriate to consider charge-offs, since these may align better with the actual loan loss situation in a given period. Hence I add provisions for loan and lease losses back to the net income and subtract the originally excluded charge-offs. The same logic applies to transfer risk reserves, which is a position that accounts for risks relating to debt service by foreign borrowers stemming from a lack of convertibility of the local currency. General risk provisions are not reported on the Call Report and hence do not enter into the calculation. When computing bank capital invested, the adjustments mirror the adjustments made to net income. Specifically, nonrecurring events (disguised financial expenses) are capitalized (amortized) over a five year period (Fiordelisi, 2007). Here, the 5-year moving sum (5-year moving average) of "other noninterest expense" proxies for capitalized (amortized) R&D expense, training expense and operating lease expense. The assumption behind amortization is straight line depreciation. Deferred tax debits and credits are not reported on the Call Reports and hence omitted. Finally, stocks corresponding to other flow positions which are excluded from economic profits, such as loan loss provisions, are added to capital invested in order to account for their nature as a funding source and by allocating a corresponding capital charge (Uyemura, Kantor and Pettit, 1996). With economic profits and capital invested in hand, the only remaining component of EVA is the cost of capital.

Estimating the cost of capital is a contentious issue in the literature (Fama and French, 1997). A standard method used for this purpose is the weighted average cost of capital (WACC) approach (see for example Miles and Ezzell, 1980). This approach postulates that the firm's cost of capital is a linear combination of the cost of equity and the cost of debt. The cost of equity is usually estimated from models of stock returns such as the capital asset pricing model (Sharpe, 1964), the arbitrage pricing theory (see for example Ross, 1976) or a multifactor model (see for example Fama and French, 1993). The cost of debt can be based on the promised interest rate. However, as Cooper and Davydenko (2007) show, it may need to be adjusted for the riskiness of debt. In the context of banks, however, Fiordelisi (2007) argues that the WACC approach may not be appropriate. Thus, for banks, costs relating to liabilities are primarily productive costs and only partly reflect cost of financing. In contrast, they would routinely be classified as financial cost in industrial firms. This is because the main economic function of banks is to act as intermediaries. They intermediate funds to the wider economy by, for example, transforming large numbers of small deposit units into large units of loans, as well as by transforming duration and risk. Therefore their core business involves making and receiving interest payments. In datasets such as the Call Report, it is not possible to clearly separate the cost of funds into financing and productive components. In order to avoid arbitrary assumptions in this context, this thesis follows Fiordelisi and Molyneux (2007) and Fiordelisi and Molyneux (2010) amongst others and defines the cost of capital purely on the basis of equity. This is a sensible assumption because equity capital is one of the sources of funding that banks and regulators are likely to target explicitly since it protects the intermediary from financial distress (see for example McAllister and McManus, 1993). Finally, it is also likely that this simplifying assumption will have only a limited effect on the final results. This is because the component of interest expenses to be attributed to non-core activities is likely to be small relative to the majority of interest expenses that are related to productive assets.

In estimating the cost of capital this thesis follows Ünal and Kane (1988a), Ünal and Kane (1988b) and Stone (1974) and uses a market model for listed banks. Specifically, I obtain monthly stock return data on listed banks (primarily holding companies), data on market returns[6] and data on long term interest rate index returns (30yr bond returns) from CRSP. The betas are estimated using three years of data. These estimated coefficients allow for the calculation of expected excess returns and thus the cost of equity capital. Subsequently, I merge these returns with Bank COMPUSTAT data by way of the CRSP-FRB matching table provided by the New York Branch of the Federal Reserve (New York Federal Reserve Bank, 2012). This step is necessary in order to obtain balance sheet data on the listed banks that contribute to the calculation of cost of equity capital. The next step merges the cost of capital on to the Call Report data, directly for commercial banks that are either listed or are subsidiaries of listed banks. For the remaining banks the holding company data are stratified at the 20, 40, 60, 80 and 95$^{\text{th}}$ percentiles of the asset size distribution.[7] Using the same absolute size cutoffs on the Call Report data allows one to assign to commercial banks within a given size stratum the average cost of capital from the corresponding bank holding company size stratum. Finally, for banks that cannot be matched by this procedure I assign the average cost of capital computed over all listed banks. This approach essentially follows Fiordelisi (2007). The main advantage of this approach is that it allows for a computation of plausible cost of capital values for a broad population of banks with only minimal assumptions.

2.3.3. Data Selection and Filtering

Finally, this section comments on the data selection and filtering methodology that is used to generate the data set. Ultimately, the sample should preserve as many observations as possible, while removing outliers that may drive results due to data entry errors or idiosyncrasies of single observations. In the context of efficiency orientated

[6] S&P value weighted returns excluding dividends. The results are robust to the in and exclusion of dividends, to the use of equal or value weighted indices and to the use of S&P vs. NYSE/AMEX indices.

[7] A finer granularity such as deciles at this level does not fundamentally change results.

studies outliers are in particular bank observations, which exhibit negative values for inputs, outputs or prices since such values are implausible (see for example Asaftei, 2008 and Wheelock and Wilson, 2001). Furthermore, a certain threshold as to interest rate related prices can safely be assumed. For example Wheelock and Wilson (2001) delete from their sample banks that exhibit interest costs exceeding 25% p.a.. In addition, many studies impose minimum size requirements on their sample (for example Bauer, Berger, Ferrier and Humphrey, 1998, Berger and Bouwman, 2009, Feng and Serletis, 2009, Feng and Serletis, 2010 and Mitchell and Onvural, 1996) or focus on a minimum period of existence (for example Asaftei, 2008, Bauer, Berger, Ferrier and Humphrey, 1998, DeYoung, Spong and Sullivan, 2001, Feng and Serletis, 2009 and Feng and Serletis, 2010).

Based on this literature, this thesis eliminates bank-year observations:

1. with missing values in the critical variables,
2. with less than USD 10 m in assets,
3. with negative book value,
4. with implausible values such as negative input- or output- quantities or negative prices,
5. with equity/asset ratios of less than 1% or greater than 100%,
6. with return on equity $>$ 1 or return on equity $<$ -1,
7. if a bank has no commercial real estate or no commercial industrial loans outstanding,
8. and if either residential or consumer loans constitute more than half of the loan portfolio.

The asymmetrical treatment of small banks is due to the fact that very large banks are likely to be much more representative of the technology prevailing in the banking markets than are extremely small banks. To the contrary, extremely small banks, for example due to the heavy influence of the owner or due to extremely localized banking activities, may employ quite exotic strategies compared to the population of banks. Negative book value and equity over asset ratios below 1% may indicate either data entry errors or extreme distress, either of which would contaminate the dataset with undue noise. Negative prices or input-/output quantities are not plausible and likely due to errors in the data. Excessive returns are likely to be indicative of either distress or atypical observations. Ultimately, this leads to an unbalanced sample with 118,164 bank-year observations between the years 1994-2010. This order of magnitude is above the median of similar studies but comparable to the literature studying US banks and in line with the number of banks reported by, for example, Tregenna (2009).

3. Shareholder Value Efficiency: Methods and Evidence from the US Banking Industry

This chapter formalizes the GFA method and applies it to the parametrization of economic frontiers in the banking sector. This serves to both validate the new method on real world data and to investigate some questions of economic interest. I use this new method to estimate shareholder value efficiency of US banks using a large sample encompassing 118,164 bank year observations. Results across a number of statistical and economic criteria show that the GFA method provides valid efficiency scores. GFA explains a greater proportion of the value creation of US banks and is economically more significant than stochastic frontier analysis, in particular when the shape of the production function varies by bank size. Additionally, shareholder value efficiency is found to be more important in explaining value creation than both conventional efficiency measures and managerial ability. This provides further support for the SHVE concept.

3.1. Introduction

Economic measures of efficiency, such as cost efficiency, provide information on the extent to which banks and their managers are able to choose inputs efficiently so as to minimize the cost of producing a given output bundle relative to the industry technology. Analogously, the related concepts of revenue and profit efficiency describe similar phenomena. The literature has focused on efficiency measures because these allow comparisons between economic entities using varying input and output bundles. From the perspective of shareholders, however, these economic quantities may not always accurately align with their objective functions, since these stakeholders are primarily motivated by value creation. It is likely that cost, revenue or even profit efficiency, albeit necessary, are not sufficient conditions for value to be created efficiently.[1]

Fiordelisi (2007) has formulated the concept of shareholder value efficiency (SHVE), which may be efficacious in mitigating these issues. However, the SHVE concept has previously been operationalized by stochastic frontier analysis (SFA), which as a method is not without limitations. Hence this chapter contributes to the discussion in four ways. First, it develops and tests the GFA method for efficiency measurement. Second, it applies this method to shareholder value efficiency and compares its performance with stochastic frontier analysis across a broad set of criteria. The results thus provide an important check on the plausibility of the shareholder value efficiency concept. Furthermore shareholder value efficiency has so far only been studied in the European context. Hence the third contribution of this chapter is to provide first evidence on the shareholder value efficiency of US banks. Fourth, this analysis is the first to establish a link between value creation and managerial ability for banks. The sample covers virtually the entire population of US commercial banks and contains 118,164 bank-year observations during the years 1994 through 2010.

Banks face an essential trade-off between risk-taking and value creation. Shareholder value efficiency has been linked to value creation (Fiordelisi and Molyneux, 2010). Furthermore, banks that underperform in terms of value creation have been found to be more risky (Cipollini and Fiordelisi, 2012). These findings suggest that shareholder value efficiency might be an important concept that can capture these significant dimensions of bank behavior. The shareholder value efficiency metric indicates how well a bank's management chooses its input and output mix so as to optimize value creation relative to the latent transformation function spanned by its industry peers. Shareholders aim for value maximization within the bounds imposed by technology and competition. Therefore this measure likely aligns better with their objective functions than conventional efficiency measures. However, if banks faced homogeneous economic, regulatory and competitive conditions and if, in addition, managers' and owners' interests were fully aligned, managerial ability should be a better indicator of bank value creation than SHVE because, in this setting, more able managers would automatically run more valuable banks. In this case, managerial ability would be a better indicator of bank value creation than SHVE and the SHVE concept would be redundant. The presence of

[1]As an example consider the case where excessive cost saving efforts negatively impact the ability of a bank to screen loans, such that the ensuing losses exceed the initial cost savings. Further misalignment between conventional efficiency and value creation may be due to other factors such as agency problems (see Berger and Bonaccorsi di Patti, 2006, Hughes, Lang, Mester, Moon and Pagano, 2003, Jensen and Meckling, 1976).

these idealized conditions is always a question of degree and is at the same time difficult to estimate directly. Therefore it is important to investigate the information content of SHVE vis-à-vis managerial ability when it comes to explaining value creation in US banks. This chapter provides this validation exercise.

The received parametrization of SHVE relies on stochastic frontier analysis to generate a frontier that explains value creation, as proxied by economic value added (EVA), by way of a Translog production function parametrized in terms of input quantities and output prices. The use of SFA to parametrize shareholder value efficiency raises three main concerns, however. First, only one method (SFA) for the parametrization of the shareholder value efficiency measure is available.[2] However, since efficiency is a latent concept, having an alternative parametrization method would provide decision makers with a valuable plausibility-check of SHVE scores. The need for such a check is highlighted by findings in the efficiency literature, which show that alternative parametrizations of efficiency may provide very different results (see for example Bauer, Berger, Ferrier and Humphrey, 1998, Weill, 2004 and Huang and Wang, 2002). Second, SFA postulates that the functional form linking input and output information to the economic quantity of interest is known and that inefficiency follows a known distribution. These assumptions may be justified in cases such as cost efficiency, where the applied researcher has a concrete theory available for guidance. However, no such theory is available for shareholder value creation. To the contrary, highly nonlinear patterns of value creation may result from, for example, increased tail risk due to adverse effects of earnings management (see for example Andreou, Cooper, Louca and Philip, 2013 and Balboa, López-Espinosa and Rubia, 2013). These complexities substantially reduce the likelihood that a priori parametric assumptions regarding the production function will adequately capture the underlying process.[3] Third, SFA requires a rigid classification of assets and liabilities as either inputs or outputs. However, this will ignore synergies between different asset classes as well as the dual role of certain assets, such as derivatives, that can be used by banks as both inputs and outputs. The method proposed in this chapter overcomes these restrictive assumptions.

[2] Data envelopment analysis (DEA), the natural alternative, can unfortunately not be used in the case of shareholder value efficiency. This is because economic frontiers based on DEA would require the computation of optimal shareholder value creation from the optimal, feasible input and output mix given prices. Such an approach is straightforward in the case of, for example, cost efficiency, but it is less obvious which "prices" could link input and output quantities to shareholder value (see for example, Coelli, Rao, O'Donnell and Battese, 2005).

[3] Even in the cases for which theoretical underpinnings do exist, the incompatibility of commonly assumed production functions, such as the Translog, with reality has been noted particularly for the banking sector (see e.g. Mitchell and Onvural, 1996).

Ideally, an efficiency parametrization method will have three main properties. First, it should have the capacity to find an envelope for the data that provides plausible efficiency scores that are robust to noise. Second, it should not require either prior knowledge or restrictive assumptions about the data generating process. Third, it should be able to parametrize various efficiency measures, both economic and technical. In general, such a method will consist of two components: an estimation component, whose task is to fit a production function, and a component ensuring that what is estimated is in fact a frontier and not merely an average production function.

The GFA method satisfies all of the above criteria. This method adopts a nonparametric approach to operationalize the estimation component. Specifically, it uses artificial neural networks, which have been shown to have the capacity to approximate both functions and their quantiles arbitrarily well (Hornik, Stinchcombe and White, 1989, White, 1992) for this purpose. To operationalize the frontier component the method relies on Granger's (1969) asymmetric loss functions, which have been applied for example in the field of forecasting (Christoffersen and Diebold, 1997). Instead of using artificial neural networks, any other nonlinear approximator such as kernel regression could have been used as the estimation component. This would, however, require that a compatible frontier component can be devised. Thus the GFA method is generalized in two senses. First, it does not require restrictive assumptions regarding the form of the transformation function and the distribution underlying the error terms. Second, it can be used to fit not only shareholder value efficiency but also other measures of economic and technical efficiency. The appendix to this chapter (Appendix A) demonstrates this capability by applying GFA to cost efficiency.

The main results are as follows. In the descriptive domain, this chapter examines the statistical properties of shareholder value efficiency as well as the univariate relations between SHVE and typical bank performance indicators that do not rely on frontier concepts. The results show that GFA and SFA provide similar efficiency scores, which illustrates that GFA is a viable efficiency parametrization method. However, GFA shareholder value efficiency scores tend to provide more information on the performance of US banks than do SFA scores. In the inferential domain, this chapter uses a multivariate setting to examine the economic and statistical significance of shareholder value efficiency both vis-à-vis managerial ability and cost and revenue efficiency. Findings indicate that SHVE is more informative with respect to value creation than both managerial ability and other efficiency scores. This underscores the importance of the SHVE concept. Results also show that the SFA and GFA efficiency scores contribute to the explanation of shareholder value creation independently of one another, which confirms that they capture similar but not identical information. However, more importantly, GFA is found to provide SHVE scores that are both economically and statistically more meaningful in explaining value creation than the comparable SFA-based scores. Thus, overall, these results vindicate the GFA method and validate the shareholder value efficiency concept.

The remainder of this chapter is organized as follows. The proposed generalized frontier analysis method is developed in Section 3.2. Section 3.3 discusses the data except for managerial ability, which is discussed in detail in Chapter 5; Section 3.4 presents the empirical results and Section 3.5 summarizes the robustness checks; Section 3.6 concludes.

3.2. The GFA Algorithm

This section develops the GFA algorithm. As has been noted in the discussion in Section 2.2.2, prior attempts at parametrizing efficient frontiers by way of ANNs face the problem that they provide average production functions by design and some ad hoc procedure must be adopted to obtain efficiency scores from these predictions. To illustrate the general problem, consider Figure 3.1. The transparent surface describes the theoretical maximum level of output implied by the production technology, while the noisy surface describes the actually observed level of output y, both on the third axis. The x-y-plane denotes the input quantities, $\mathbf{x}_i$, used by each bank, i. The task is to recover the transparent surface from the noisy observed data. More formally, assume that by training an artificial neural network on the available data on inputs for each bank i, $\mathbf{x}_i$, one has obtained some hypothesis $h(\mathbf{x}_i)$ about the true value of the output y_i.

Then, in the spirit of Equation 2.6 and following Athanassopoulos and Curram (1996), a naïve way of defining technical efficiency is:

$$TE_i = \frac{y_i}{h(\mathbf{x}_i)} \tag{3.1}$$

The average production function $h(\mathbf{x}_i)$ encoded by the ANN will, if it has been learned well, have a very similar shape as the transparent frontier. However, it will pass through the center of mass of the noisy data because that is all the ANN has access to in terms of learning. Therefore, assuming that noise is normally distributed, it will lie above or below the observed data about half the time. Then, for about half of the observations in the sample, efficiency will be greater than unity, which makes little sense conceptually.

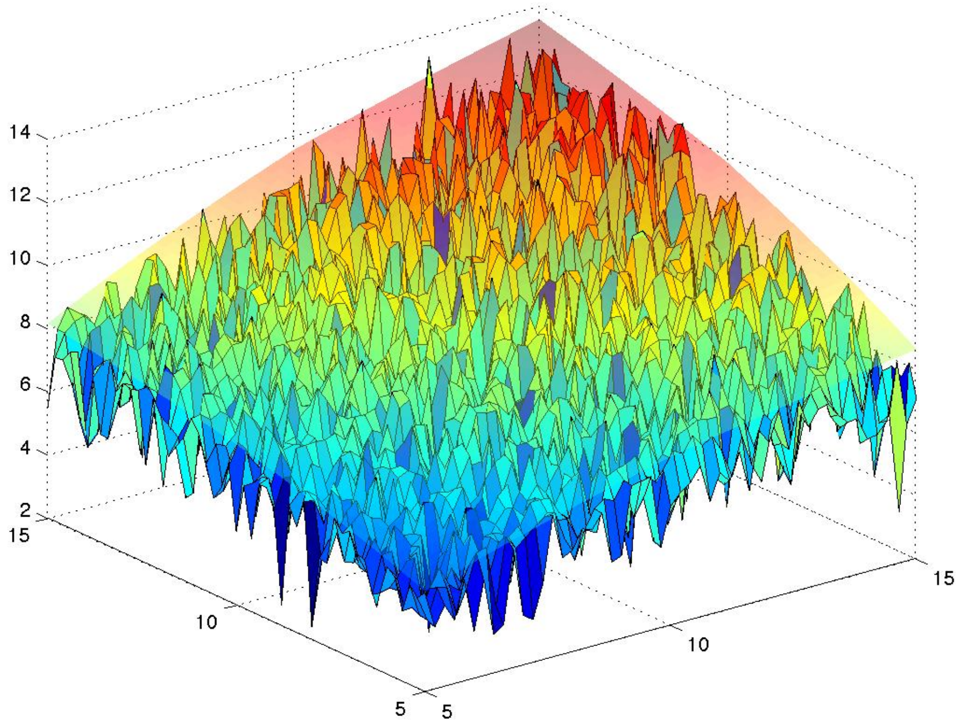

Figure 3.1.: Theoretical Output and Observed, Noisy Output.

The x and y coordinates represent the input space, while the z coordinate represents the output space of a two input single output Cobb-Douglas technology. The transparent, smooth surface represents the theoretical level of output, while the jagged surface represents the actual observed output.

Realizing this problem, Athanassopoulos and Curram (1996) propose a simple solution, which they refer to as standardized frontier. Specifically, for all observations one simply defines the prediction error of the average production function as $\boldsymbol{\epsilon} = \mathbf{y} - h(\mathbf{X})$ and lets standardized efficiency be

$$TE_i^n = \frac{y_i}{(h(\mathbf{x}_i) + \max(\boldsymbol{\epsilon}))}, \tag{3.2}$$

where the max operation denotes the maximum norm of the vector $\boldsymbol{\epsilon}$. Then all efficiency scores will be bounded by unity from above. This approach is reminiscent of the corrected ordinary least squares estimation of deterministic production frontiers (see Kumbhakar and Lovell, 2003, pp.70-71). A third concept for the operationalization of efficiency with ANNs is proposed by e.g. Santín (2008). This approach is similar in spirit to that above, however the definition of the error term is slightly different. Here the shift to the predicted production function is applied over finite batches of observations by an iterative procedure. Having sorted the predicted output values $h(\mathbf{x}_i)$ from smallest to largest, one considers the errors. If the error is non-negative one increments the predicted values by the error value. If the error is negative, one considers the next error value until a positive value is found. Once this is the case, all predicted values between and including the one corresponding to the first negative observed error are incremented by this positive value. In effect, the shift in the frontier is carried out piecewise. It is clear that the approach proposed by Santín (2008) will lead to a very large number of observations on the frontier. It seems unlikely that this will be an accurate representation of reality. The second drawback of Athanassopoulos and Curram's (1996) and Santín's (2008) methods of shifting the average production function outward to obtain a frontier is its arbitrariness. There is no apparent reason why the maximum prediction error made on a subset or across all observations should impact a number of other banks in the sample as well.

This arbitrariness of this approach can be eliminated by introducing the GFA method. The intuition behind this approach can be illustrated as in Figure 3.2. The approach of Athanassopoulos and Curram (1996) uses information on input quantities x to infer a "Frontier", $h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(x)$, here visualized in blue. This causes no conceptual problems for observations such as A. This firm is clearly located below the frontier and hence inefficient. However observation B is more puzzling. Given that it is located above the frontier it would have to be called "superefficient" and would be assigned an efficiency score greater than one. But efficiency scores greater than unity make little conceptual sense. To overcome this problem, the authors resort to arbitrary shift mechanisms as described above.

GFA resolves this issue in a far less arbitrary way. Specifically, this approach recognizes that observations like A are conceptually sane but that observations like B make little sense. To accommodate this feature of the modeling situation, GFA splits the process of fitting a frontier into two components: the frontier and the estimation component. It maintains the desirable, flexible, nonparametric characteristics of artificial neural networks in the estimation component. However, in order to ensure that the estimation process accommodates observations like B in a natural way, it modifies the loss function of the artificial neural network. More specifically, "superefficient" firms are penalized asymmetrically more than regular, inefficient firms. This forces the ANN to fit a frontier rather than an average production function. This modification allows the net to efficiently exploit the information about the shape of the error surface as yielded by the backpropagation algorithm while at the same time ensuring that the frontier is closer to more efficient banks and further from less efficient ones. Thus the GFA algorithm provides a nonparametric, stochastic alternative to SFA and DEA, uniting the advantages of both these methods.

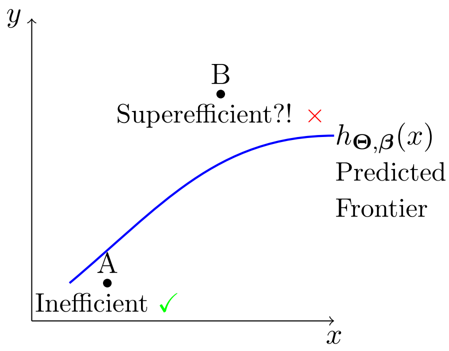

Figure 3.2.: Estimating Frontiers.

Schematic representation of an average production function $h_{\mathbf{\Theta},\boldsymbol{\beta}}(x)$ given information on a single input x and corresponding output y for two observations (black circles), A and B.

To illustrate precisely how the GFA method improves on previous approaches, it is necessary to introduce some theory related to artificial neural networks to facilitate the exposition. A feed forward ANN is characterized by its architecture, which is defined by a set of units, or neurons, that are organized in layers and matrices of weights connecting each unit in each layer layer to each unit in the preceding one. Each neuron is a computational unit, which takes the sum of the inputs, computes the corresponding value of a so-called activation function and outputs the result. The first layer, which takes the raw data as its inputs, is correspondingly called input layer, the last layer gives the result of the hypothesis for a particular sample of data and is therefore called output layer. All other layers are called hidden layers. It is customary to attach a so-called bias unit to each layer. This is a unit which takes no input and which outputs a constant value of +1, so that it can be thought of as a constant term on each level of the hypothesis. A particular instance of an ANN is represented in Figure 3.3. Here the ANN has one hidden layer with four hidden units (medium grey), four input units (light grey) and one output unit (dark grey). The input signal is propagated from left to right, while the error signal is propagated from right to left in order to adjust the connection weights between the units.

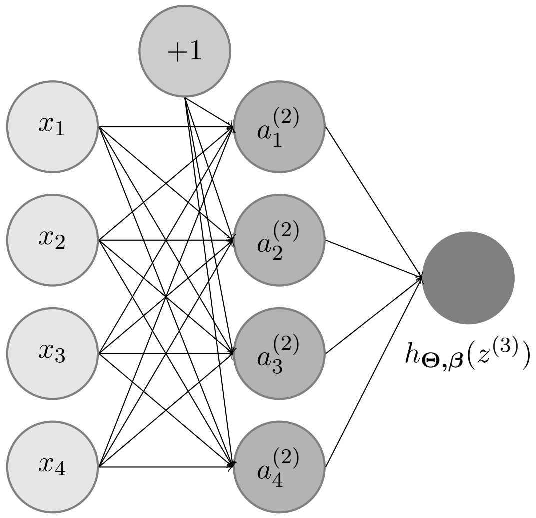

Figure 3.3.:
Schematic Diagram of ANN Architecture, Following Ng, Ngiam, Foo, Mai and Suen (2011).

Circles represent units, arrows represent weights connecting units. These are the free parameters of the network. The light grey circles represent the input layer units, the dark grey circle represents the output layer unit. The remaining circles represent the hidden layer units and the bias unit (marked "+1"). Information is passed through the network from left to right. x stands for an input signal, a stands for the activation of the unit, computed by applying an activation function g to the sum of the incoming signals z. $h_{\boldsymbol{\Theta},\boldsymbol{\beta}}$ represents the hypothesis of the network about the true target value, $\mathbf{y}$, corresponding to the input vector $\mathbf{x}$.

More formally, assume the input layer has p, the hidden layer has q and the output layer has r units and that a bias unit is added to each hidden layer. Given the p dimensional input vector $\mathbf{x}$, the $q \times p$ weight matrix $\boldsymbol{\Theta}^{(1)}$ connecting the input layer and the hidden layer as well as the $r \times q$ weight matrix $\boldsymbol{\Theta}^{(2)}$ connecting the hidden layer and the output layer, plus a corresponding bias unit connected by the vector $\boldsymbol{\beta}^{(1)}$ $(q \times 1)$, the input of the hidden layer can be computed as

$$\mathbf{z}^{(2)} = \boldsymbol{\Theta}^{(1)}\mathbf{x} + \boldsymbol{\beta}^{(1)}. \tag{3.3}$$

This will yield a $q \times 1$ dimensional vector $\mathbf{z}^{(2)}$, which constitutes the input signal at the hidden layer. The units of the hidden layer then compute the activation by applying the activation function $g = \frac{1}{(1+\exp(-z))}$ to the input so that the activation of the hidden layer is given by:

$$\mathbf{a}^{(2)} = g(\mathbf{z}^{(2)}). \tag{3.4}$$

Then one obtains the $q \times 1$ input of the output layer as

$$\mathbf{z}^{(3)} = \mathbf{\Theta}^{(2)}\mathbf{a}^{(2)}. \tag{3.5}$$

The network forms a hypothesis, $h_{\mathbf{\Theta}^{(1)},\mathbf{\Theta}^{(2)},\boldsymbol{\beta}^{(1)}}(\mathbf{x})$ about the true, observed value $\mathbf{y}$. The hypothesis is the output of the ANN given the input data $\mathbf{x}$ and the current weights $\mathbf{\Theta}^{(1)}, \mathbf{\Theta}^{(2)}, \boldsymbol{\beta}^{(1)}$. Then the activation of the output layer, which corresponds to the hypothesis, is given by:

$$\mathbf{a}^{(3)} = h_{\mathbf{\Theta}^{(1)},\mathbf{\Theta}^{(2)},\boldsymbol{\beta}^{(1)}}(\mathbf{z}^{(3)}) = g(\mathbf{z}^{(3)}). \tag{3.6}$$

This process of passing a set of inputs to the network and then propagating these throughout the layers is commonly referred to as forward propagation. The actual fitting of the network to the data, however, entails the modification of the entries of the weight matrices, $\mathbf{\Theta}, \boldsymbol{\beta}$. This occurs by the reverse of forward propagation, so that the algorithm is called backpropagation in the literature. A brief exposition of this procedure follows. A more extensive derivation and discussion can be found in Haykin (1999) or in Ng, Ngiam, Foo, Mai and Suen (2011).

At the outset consider the penalty function, also known as cost or loss function, for a neural network. This function attaches a numerical value to the prediction errors made by the net such that this value describes the goodness of the prediction relative to the actually observed values. Assume that the network being considered has L layers, each of which has s_l units, not counting bias units. For ease of notation let $\mathbf{\Theta}, \boldsymbol{\beta}$ represent the free parameters of the ANN for all layers. A common choice in the literature is the squared error metric as the kernel for the cost function. For one training case this is given as:

$$SE(\mathbf{\Theta}, \boldsymbol{\beta}, \mathbf{x}, \mathbf{y}) = \frac{1}{2} \parallel (h_{\mathbf{\Theta},\boldsymbol{\beta}}(\mathbf{x}) - \mathbf{y}) \parallel^2, \tag{3.7}$$

where $\mathbf{x}$ represents the input signal and $\mathbf{y}$ represents the target value. Assume that the parameters are subject to regularization (Gnecco and Sanguineti, 2009). This procedure, sometimes called weight decay, is similar to ridge regression. Weight decay is helpful in preventing the excessive growth of individual weights and thus facilitates generalization. Then the cost, or loss, function with weight decay λ can be defined over all m training cases as:

$$C(\mathbf{\Theta}, \boldsymbol{\beta}, \mathbf{X}, \mathbf{Y}, \lambda) = \frac{1}{m}\sum_{k=1}^{m} SE(\mathbf{\Theta}, \boldsymbol{\beta}, \mathbf{x}^k, \mathbf{y}^k) + \frac{\lambda}{2}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\left(\mathbf{\Theta}_{ji}^{(l)}\right)^2. \tag{3.8}$$

The first term sums the squared errors for all training cases $k = 1$ up to m. The second term now sums the squares of the weights for all layers. For each layer consider each weight from each unit in layer l to each unit in layer $l+1$. Note that the notation $\boldsymbol{\Theta}_{ji}^{(l)}$ signifies the weight in the weight matrix corresponding to layer l which connects unit i in layer l to unit j in layer $l+1$. It is ultimately the aim to iteratively update these weights such that the value of the loss function associated with the ANN's prediction will become minimal. A common way of training the network is by way of gradient descent with learning rate μ. Then for a layer l one can update the weights as follows:

$$\boldsymbol{\Theta}_{ji}^{(l)} = \boldsymbol{\Theta}_{ji}^{(l)} - \mu \frac{\partial C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}, \mathbf{y}, \lambda)}{\partial \boldsymbol{\Theta}_{ji}^{(l)}}. \tag{3.9}$$

Similarly, for the bias weights:

$$\boldsymbol{\beta}_{j}^{(l)} = \boldsymbol{\beta}_{j}^{(l)} - \mu \frac{\partial C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}, \mathbf{y}, \lambda)}{\partial \boldsymbol{\beta}_{j}^{(l)}}. \tag{3.10}$$

The backpropagation algorithm serves the purpose of efficiently computing the partial derivatives needed for the update of the weights. The computation of the desired partials is developed next, following Haykin (1999). Define the error that the neural net makes at the output layer for one observation as:

$$\boldsymbol{\epsilon}(\mathbf{x}) = h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}) - \mathbf{y}. \tag{3.11}$$

To enable the use of gradient descent at reasonable computational cost, it is necessary to compute the partial derivatives of the cost function with respect to each individual weight. Since the partial of the weight decay term is straightforward, the subsequent discussion focusses on the SE component of the loss function. Specifically, consider a general cost function of the form $C(h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}), \mathbf{y})$ (subsequently abbreviated as $C(.)$) that depends on the prediction and the desired target value. Then one can write for the change in the loss function resulting from a marginal change in the weight connecting neurons j and i in layers $l+1$ and l:

$$\frac{\partial C(.)}{\partial \boldsymbol{\Theta}_{ji}^{(l)}} = \frac{\partial C(.)}{\partial \boldsymbol{\epsilon}_{j}^{(l+1)}} \frac{\partial \boldsymbol{\epsilon}_{j}^{(l+1)}}{\partial \mathbf{a}_{j}^{(l+1)}} \frac{\partial \mathbf{a}_{j}^{(l+1)}}{\partial \mathbf{z}_{j}^{(l+1)}} \frac{\partial \mathbf{z}_{j}^{(l+1)}}{\partial \boldsymbol{\Theta}_{ji}^{(l)}}. \tag{3.12}$$

This expression follows from applying the chain rule multiple times. First, the change in the cost function of the network depends on the change of the cost function as one varies the error at unit j in the output layer ($\frac{\partial C}{\partial \boldsymbol{\epsilon}_j}$) and this depends on the variation in the error as one varies the weight connecting neuron i in the previous layer to neuron j in the output layer ($\frac{\partial \boldsymbol{\epsilon}_j}{\partial \boldsymbol{\Theta}_{ji}}$). Then this latter expression is itself the product of the variation in the error as one varies the activation ($\frac{\partial \boldsymbol{\epsilon}_j}{\partial \mathbf{a}_j}$) multiplied by the variation in the activation as one varies the weight ($\frac{\partial \mathbf{a}_j}{\partial \boldsymbol{\Theta}_{ji}}$). Finally, this last expression depends on how the activation varies as one varies the incoming signal ($\frac{\partial \mathbf{a}_j}{\partial \mathbf{z}_j}$) and how that signal varies as one varies the weight ($\frac{\partial \mathbf{z}_j}{\partial \boldsymbol{\Theta}_{ji}}$). Decomposing the expressions one by one gives:

$$\frac{\partial \boldsymbol{\epsilon}_j^{(l+1)}}{\partial \mathbf{a}_j^{(l+1)}} = 1, \tag{3.13}$$

$$\frac{\partial \mathbf{a}_j^{(l+1)}}{\partial \mathbf{z}_j^{(l+1)}} = g'(\mathbf{z}_j^{(l+1)}), \tag{3.14}$$

and

$$\frac{\partial \mathbf{z}_j^{(l+1)}}{\partial \boldsymbol{\Theta}_{ji}^{(l)}} = \mathbf{a}_i^{(l)}. \tag{3.15}$$

Substituting back into Equation 3.12 gives:

$$\frac{\partial C(.)}{\partial \boldsymbol{\Theta}_{ji}^{(l)}} = \frac{\partial C(.)}{\partial \boldsymbol{\epsilon}_j^{(l+1)}} g'(\mathbf{z}_j^{(l+1)})\mathbf{a}_i^{(l)}. \tag{3.16}$$

Then, with learning rate μ, one can adjust the weights according to the “delta rule”:

$$\Delta \boldsymbol{\Theta}_{ji}^{(l)} = -\mu \boldsymbol{\delta}_j^{(l+1)} \mathbf{a}_i^{(l)}, \tag{3.17}$$

with

$$\begin{aligned}\boldsymbol{\delta}_j^{(l+1)} &= \frac{\partial C(.)}{\partial \boldsymbol{\epsilon}_j^{(l+1)}} \frac{\partial \boldsymbol{\epsilon}_j^{(l+1)}}{\partial \mathbf{a}_j^{(l+1)}} \frac{\partial \mathbf{a}_j^{(l+1)}}{\partial \mathbf{z}_j^{(l+1)}} \\ &= \nabla_{\boldsymbol{\epsilon}_j^{(l+1)}} C(.) g'(\mathbf{z}_j^{(l+1)}),\end{aligned} \tag{3.18}$$

and ∇ denoting the partial derivative operator of the argument with respect to the subscript. This notation will be useful when considering the gradient of vector valued functions such as in Equation 3.21. This works straightforwardly when $l + 1 = L$. However, for hidden layers it is not obvious what the desired output value for each hidden neuron is. Therefore computation of $\boldsymbol{\epsilon}^{(l+1)}$ requires the “backpropagation of errors". Letting $l+1 = L-1$, for instance, rewrite $\boldsymbol{\delta}_j$ as:

$$\begin{aligned}\boldsymbol{\delta}_j^{(L-1)} &= \frac{\partial C(.)}{\partial \mathbf{a}_j^{(L-1)}} \frac{\partial \mathbf{a}^{(L-1)}}{\partial \mathbf{z}^{(L-1)}} \\ &= \nabla_{\mathbf{a}_j^{(L-1)}} C(.) g'(\mathbf{z}_j^{(L-1)}). \end{aligned} \tag{3.19}$$

Then the value of the cost function C depends on the error at all $t = 1, \ldots, s_L$ neurons in layer L as previously defined (see Equation 3.18). The partial with respect to $\mathbf{a}_j^{(L-1)}$ can be rewritten as:

$$\begin{aligned}\frac{\partial C(.)}{\partial \mathbf{a}_j^{(L-1)}} &= \sum_t \nabla_{\boldsymbol{\epsilon}_t^{(L)}} C(.) \frac{\partial \boldsymbol{\epsilon}_t^{(L)}}{\partial \mathbf{a}_j^{(L-1)}} \\ &= \sum_t \nabla_{\boldsymbol{\epsilon}_t^{(L)}} C(.) \frac{\partial \boldsymbol{\epsilon}_t^{(L)}}{\partial \mathbf{z}_t^{(L)}} \frac{\partial \mathbf{z}_t^{(L)}}{\partial \mathbf{a}_j^{(L-1)}}. \end{aligned} \tag{3.20}$$

Note that $\boldsymbol{\epsilon}^{(L)} = g(\mathbf{z}^{(L)}) - \mathbf{y}$ and $\mathbf{z}^{(L)} = \boldsymbol{\Theta}^{(L-1)} \mathbf{a}^{(L-1)}$, which allows one to write (using matrix calculus notation):

$$\begin{aligned}\frac{\partial C(.)}{\partial \mathbf{a}^{(L-1)}} &= \boldsymbol{\Theta}^{(L-1)T} (\nabla_{\boldsymbol{\epsilon}^{(L)}} C(.) \bullet g'(\mathbf{z}^{(L)})) \\ &= \boldsymbol{\Theta}^{(L-1)T} \boldsymbol{\delta}^{(L)}. \end{aligned} \tag{3.21}$$

Here $\bullet$ is used to denote componentwise multiplication of two matrices, also known as the Hadamard product. The superscript ^{T} signifies transposition. Now using the earlier definition 3.19 one can write:

$$\begin{aligned}\boldsymbol{\delta}^{(L-1)} &= \nabla_{\mathbf{a}^{(L-1)}} C(.) \bullet g'(\mathbf{z}^{(L-1)}) \\ &= \boldsymbol{\Theta}^{(L-1)T} \boldsymbol{\delta}^{(L)} \bullet g'(\mathbf{z}^{(L-1)}), \end{aligned} \tag{3.22}$$

which defines a recursion that can be applied to any hidden layer. This enables one to compute the gradients and thus the desired weight changes. Then the partial derivatives of the cost function with respect to any weight can, in analogy to Equations 3.16 and 3.18, be expressed as:

$$\frac{\partial C(.)}{\partial \boldsymbol{\Theta}_{ji}^{(l)}} = \boldsymbol{\delta}_j^{(l+1)} \mathbf{a}_i^{(l)}. \tag{3.23}$$

For $\boldsymbol{\beta}_j^{(l)}$ the analogous expression to 3.15 reduces to unity because that is the constant output of the bias unit. Therefore:

$$\frac{\partial C(.)}{\partial \boldsymbol{\beta}_j^{(l)}} = \boldsymbol{\delta}_j^{(l+1)}. \tag{3.24}$$

With these results in hand, one can write down the gradient descent algorithm with backpropagation, which has been devised so as to efficiently cycle through the data, and thus update the parameters of the ANN. Assuming the forward pass has been performed and that the activations at each layer are available, gradient descent, using backpropagation for the computation of the partials, can be carried out for one iteration over the data as summarized in Algorithm 3.1. After randomly initializing the weights, which

Algorithm 3.1 Gradient Descent with Backpropagation Algorithm

Set $\Delta\boldsymbol{\Theta}^{(l)} := \mathbf{0} \wedge \Delta\boldsymbol{\beta}^{(l)} := \mathbf{0}\ \forall l$
for $k = 1 : m$ **do**
$\triangleright$ Compute $\nabla_{\boldsymbol{\Theta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda)$ and $\nabla_{\boldsymbol{\beta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda)$ by backpropagation:
  $\boldsymbol{\delta}^{(L)} = \nabla_{\boldsymbol{\epsilon}^{(L)}} C(.) \bullet g'(\mathbf{z}_k^{(L)})$
  for $l = L - 1 : 1$ **do** $\triangleright$ Compute $\boldsymbol{\delta}^{(l)}$
    $\boldsymbol{\delta}^{(l)} = (\boldsymbol{\Theta}^{(l)})^T \boldsymbol{\delta}^{(l+1)} \bullet (\mathbf{a}_k^{(l)} \bullet (\mathbf{e} - \mathbf{a}_k^{(l)}))$ $\triangleright$ Here $\mathbf{e}$ is a vector of ones.
    $\nabla_{\boldsymbol{\Theta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda) = \boldsymbol{\delta}^{(l+1)} (\mathbf{a}_k^{(l)})^T$
    $\nabla_{\boldsymbol{\beta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda) = \boldsymbol{\delta}^{(l+1)}$
  end for
  Set $\Delta\boldsymbol{\Theta}^{(l)} := \Delta\boldsymbol{\Theta}^{(l)} + \nabla_{\boldsymbol{\Theta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda)\ \forall l$
  Set $\Delta\boldsymbol{\beta}^{(l)} := \Delta\boldsymbol{\beta}^{(l)} + \nabla_{\boldsymbol{\beta}^{(l)}} C(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}_k, \mathbf{y}_k, \lambda)\ \forall l$
end for
$\boldsymbol{\Theta}^{(l)} = \boldsymbol{\Theta}^{(l)} - \mu \left[\left(\frac{1}{m} \Delta\boldsymbol{\Theta}^{(l)} \right) + \lambda \boldsymbol{\Theta}^{(l)} \right]\ \forall l$ $\triangleright$ Update the parameters
$\boldsymbol{\beta}^{(l)} = \boldsymbol{\beta}^{(l)} - \mu \left(\frac{1}{m} \Delta\boldsymbol{\beta}^{(l)} \right)\ \forall l$

is necessary in order to break symmetrical patterns in the weights because these can induce a stagnation in the learning process (Nguyen and Widrow, 1990), this algorithm allows one to update the network weights in a way, which facilitates the learning of complex nonlinear hypotheses from the data. This idea was first developed by Werbos (1974) and further elaborated by Rumelhart and McClelland (1986). While many extensions and modifications have been proposed in the literature since, the backpropagation approach still continues to be used frequently. For a discussion see for example Bengio and Frasconi (1994), Parekh, Yang and Honavar (2000) or Hinton and Salakhutdinov (2006). However, if in the present context one were to use this algorithm to update the weights, $\boldsymbol{\Theta}, \boldsymbol{\beta}$, until convergence the result would be an average production function.

This is not a frontier but a function that approximates the available data on inputs and outputs as well as possible subject to the architecture of the network and the number of training iterations. Hence, in order to obtain a frontier, it is necessary to modify the loss function. To do so I introduce the notion of "asymmetric cost functions".

The use of asymmetric cost functions in forecasting has been known at least since the work of Granger (1969). This approach involves using an error metric that is different from the sum of squared errors as the cost function in ANN training. The formal proof in White (1992) underpins this approach. It builds on his earlier proof of the general approximation ability of ANNs and shows that ANNs with appropriately modified loss functions can be used as universal quantile estimators. Applications of asymmetric cost functions in the case of ANNs are few in number. Crone (2002, 2003) shows the expansion of the standard backpropagation algorithm used in ANN training for the computation of the derivatives of the net with respect to individual weights, for asymmetric cost functions. In fact, the only derivative that is affected by the asymmetry in the cost function is that of the output layer. Hence the discussion on the preceding pages can be directly applied to this problem. He provides an empirical application for the so called *LINLIN* cost function (see for example Christoffersen and Diebold, 1996, 1997) which consists of two linear branches starting at the origin, each of which has different slopes in the positive and negative direction:

$$LINLIN = \begin{cases} a|\hat{y} - y| & \text{if } y > \hat{y} \\ 0 & \text{if } y = \hat{y} \\ b|\hat{y} - y| & \text{if } y < \hat{y}, \end{cases} \tag{3.25}$$

where $\hat{y}$ denotes the prediction and a, b are constants. In later work Crone (2010) shows the use of the so called $QUADQUAD$ cost function:

$$QUADQUAD = \begin{cases} a(\hat{y} - y)^2 & \text{if } y > \hat{y} \\ 0 & \text{if } y = \hat{y} \\ b(\hat{y} - y)^2 & \text{if } y < \hat{y}. \end{cases} \tag{3.26}$$

Using such a cost function will induce the ANN to learn a "biased" predictor of the target data. In the case of efficiency precisely this is the aim, namely to learn the underlying structure of, for example, industry cost but with special emphasis on those banks which manage to keep cost low given an input output bundle. This thesis follows Crone (2002, 2003, 2010) and defines the asymmetric cost function of the neural net as follows.

$$QQ(\boldsymbol{\Theta}, \boldsymbol{\beta}, a, b, \mathbf{x}, \mathbf{y}) = \begin{cases} \frac{a}{2}||(h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}) - \mathbf{y})||^2 & \text{if } \mathbf{y} > h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}) \\ 0 & \text{if } \mathbf{y} = h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}) \\ \frac{b}{2}||(h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}) - \mathbf{y})||^2 & \text{if } \mathbf{y} < h_{\boldsymbol{\Theta},\boldsymbol{\beta}}(\mathbf{x}). \end{cases} \tag{3.27}$$

This does not change anything in the derivation of the partials needed for backpropagation except a constant factor. This function can then be substituted into C in lieu of $SE(\boldsymbol{\Theta}, \boldsymbol{\beta}, \mathbf{x}, \mathbf{y})$. In particular, for the output layer one can now, using the asymmetric cost function, write:

$$\boldsymbol{\delta}^{(L)} = \begin{cases} a(\mathbf{a}^{(L)} - \mathbf{y}) \bullet g'(\mathbf{z}^{(L)}) & \text{if } \mathbf{y} > \mathbf{a}^{(L)} \\ 0 & \text{if } \mathbf{y} = \mathbf{a}^{(L)} \\ b(\mathbf{a}^{(L)} - \mathbf{y}) \bullet g'(\mathbf{z}^{(L)}) & \text{if } \mathbf{y} < \mathbf{a}^{(L)}. \end{cases} \tag{3.28}$$

The gradient descent algorithm works identically, only that now the gradients will be pre-multiplied by a factor of a, respectively b according as the error is positive or negative. The type of asymmetry will depend on the kind of frontier that is being parametrized. In the cost efficiency case, for example, it is assumed that banks are generally producing at higher cost than optimal, while in the technical, profit, revenue and shareholder value efficiency cases one generally assumes that banks produce less of the target quantity than they could if they were fully efficient. In the asymmetric ANN this is equivalent to choosing the asymmetry parameter such that the frontier will approach the observations from below (cost efficiency) or above (all others). Hence I do not interpret as an error the prediction of higher cost (lower shareholder value etc.) than what is actually observed. Rather, this merely implies that the bank has been inefficient compared to other banks with a similar input-output-mix. However, observing a bank that has a level of cost below (shareholder value above) the predicted level would mean that this bank has been super-efficient. Since the frontier should envelop the sample of banks, I treat this case as a prediction error to be penalized. This is accomplished by setting $b > a$ ($a > b$).

Unreported preliminary analyses have been conducted to ensure that the GFA approach converges and that it does not overfit. Moreover, a grid search across 25 combinations of architecture and weight decay and 20 combinations of architecture, weight decay and asymmetry parameter have shown that the outcomes generated by GFA are quite robust to the choice of architecture and weight decay as well as to various choices of the asymmetry parameter. Hence, in the following, the ANN has a weight decay of

0.5 and ten hidden units. The asymmetry parameter is set to $a = 1000$ and $b = 1$ for shareholder value efficiency and the opposite for cost efficiency.

A practical point that must be addressed when conceptualizing the GFA approach is the choice of input signals (the vector $\mathbf{x}$) and target values ($\mathbf{y}$). Consider the case of SFA shareholder value efficiency as a starting point. Here, following Fiordelisi (2007), the frontier can be specified in terms of the economic outputs and the prices of inputs. The assumption is that bank managers aim at maximizing shareholder value by choosing the optimal input quantities given prices. However, in the context of an ANN this approach does not recommend itself. First, economically speaking, it is merely a matter of convenience to postulate that the only variables in managerial shareholder value maximization are input quantities. One could equally well suppose, and indeed this appears to be likely in practice, that managers choose both the in- and output mix under criteria of shareholder value maximization. Hence any efforts to maximize shareholder value are unlikely to be confined to the input-mix alone. This actual decision making process should be taken into account when parametrizing the frontier. Second, technically speaking, an artificial neural network is a structure that aims at recognizing patterns. Banks with different business models and markets may still charge or pay very similar "prices" on their products because these prices will correlate strongly with the overall state of the economy and the behavior of competitors.[4] Thus it appears unlikely that price information is the most meaningful in terms of recognizing patterns in the data. Rather I argue that banks are distinguished by the structure of their balance sheet. Therefore an ANN aiming at discovering an efficient frontier from the data should be parametrized in terms of in- and output quantities.

Having formalized the GFA method, the following section will provide some discussion on the data used in the analysis before the remainder of this chapter sets out to test the validity and capabilities of the GFA method.

3.3. Data and Variables

This section discusses the data and empirical strategy of this chapter. The main efficiency measurement methods have been introduced at length in Sections 2.1.1, 2.1.2 and in the preceding section.

As expounded in Chapter 2.3, this thesis adopts the intermediation approach proposed by Sealey and Lindley (1977) in order to define inputs and outputs and, in so doing, places its research in line with many prior studies. Specifically, I follow Berger

[4]See for example Section 2.3.1 or Berger and Bonaccorsi di Patti (2006).

(2003) in selecting as inputs labor (number of full-time-equivalent employees), purchased funds, core deposits, physical capital and equity. This thesis treats physical capital and equity as fixed inputs since these are not freely disposable in the short run. As outputs, I define consumer loans, business loans, real estate loans, securities and off-balance-sheet items. The last output category is treated as fixed, as there is no obvious flow definition that would allow a straightforward calculation of the corresponding price. In computing prices this thesis follows the localized approach of Berger and Bonaccorsi di Patti (2006), which, using information from the Summary of Deposits database, localizes banks into markets according to metropolitan statistical areas and non-metropolitan statistical area counties. Otherwise, all data related to firm-level efficiency stems from the December Call Reports for 1994-2010, available from the Chicago branch of the Federal Reserve and is cleaned as described in Section 2.3. All variables are adjusted to 2005 US dollars using the GDP implied deflator. Notably, the timespan being studied includes at least two periods of considerable turmoil in financial markets, the collapse of the "dot-com bubble" of 2000-2001 and the financial crisis of 2007-2009. One of the aims of this chapter is to analyze the validity of efficiency parametrization methods as well as the degree to which they agree or disagree. In that respect the presence of periods exhibiting high levels of noise is a welcome test of the methods under study as regards their ability to deal with such noisy data. This chapter therefore deals with the periods in question only insofar as it refrains from using panel data methods or pooled data for the estimation of efficiency. Rather, the approach is to estimate efficiency over yearly data and thus allow each efficiency parametrization method to adjust the shape of its prediction to the respective prevailing economic climate. This also ensures compatibility of the SFA and GFA results, since there are as yet no panel data extensions for GFA available.

The empirical analysis sets out to accomplish two main objectives. First, the aim is to investigate whether the proposed GFA method is able to provide a meaningful indicator of shareholder value efficiency and whether that indicator is compatible with efficiency scores derived from SFA. Second, this chapter tries to understand the information content of this indicator in terms of explaining shareholder value creation in US banks. Hence the analysis proceeds in two steps.

Since efficiency is a latent concept, the validity of efficiency scores can only be investigated indirectly. Therefore I build on Bauer, Berger, Ferrier and Humphrey (1998) in order to investigate the first objective. These authors provide a comprehensive set of consistency criteria that can be used to investigate whether different efficiency parametrizations provide plausible conclusions about the underlying technology. They propose to investigate the similarity between efficiency scores obtained from different methods along both the statistical and economic dimensions. The aim of the statistical analysis is to investigate whether the various efficiency scores have similar distributional properties, whether they provide similar rankings of banks and whether they identify similar groups of banks as particularly efficient or inefficient. The validation analysis aims to assess the degree to which efficiency scores align with the observed facts of the banking industry, and how plausibly they associate with typical nonfrontier measures of performance. While Bauer, Berger, Ferrier and Humphrey (1998) include only return, revenue and cost characteristics among these measures, this chapter expands the set of nonfrontier performance criteria to encompass the CAMELS rating criteria as completely as possible. This mnemonic represents Capital adequacy, Asset structure, Managerial ability, Earnings, Liquidity and Sensitivity. Specifically, I include return on assets (ROA) and economic value added (EVA)[5] to proxy for the earnings dimension. The analysis also includes the equity over asset ratio to proxy for the capital adequacy dimension, liquid assets over total assets to capture liquidity, and nonperforming loans over total loans to capture asset structure. I do not investigate sensitivity explicitly.

So far, the bulk of the analysis is based on rank correlations, following Bauer, Berger, Ferrier and Humphrey (1998). However, correlations, rank or otherwise, may be unstable. Therefore, in the second step, the chapter additionally investigates the information content of the two shareholder value efficiency parametrizations, using regression analysis. Specifically, it analyzes the information content of the shareholder value efficiency scores with respect to one another and vis-à-vis other efficiency scores and common control variables. It also investigates the information content of SHVE vis-à -vis managerial ability. This analysis enables insight into the value creation process in US banks.

3.4. Empirical Results

This section reports the main empirical results. Specifically, it discusses results on the statistical and economic analyses of Bauer, Berger, Ferrier and Humphrey (1998) in Sections 3.4.1 and 3.4.2. The results of the regression analyses are discussed in Section 3.4.3.

[5]In deriving this measure of shareholder value creation, I follow Fiordelisi (2007). See Section 2.3.2 for details.

3.4.1. Statistical Analysis

I turn first to the analysis of statistical properties of the two shareholder value efficiency scores. These results are reported in Table 3.1.

Panel A: Distributional Properties		
	SFA	**GFA**
mean	0.6938	0.7634
median	0.7201	0.7870
min	0.0001	-1.4005
max	0.9840	1.0000
std	0.1412	0.0896
skewness	-2.0763	-6.9785
Panel B: Correlations		
Pearson	0.4749***	
Spearman	0.4390***	
Kendall	0.3313***	
Panel C: Overlaps		
Top 25%	**Bottom 25%**	
0.4551*	0.5501*	
Top 10%	**Bottom 10%**	
0.3050*	0.5046*	
Top 5%	**Bottom 5%**	
0.2703*	0.4884*	
Top 1%	**Bottom 1%**	
0.2849*	0.3292*	

Table 3.1.:
Statistical Analysis of Shareholder Value Efficiency Parametrization Methods. This table reports results relating to the statistical analysis. Panel A shows distributional properties computed on a yearly basis and then averaged across years. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Panel B displays various correlation coefficients. Panel C reports the overlap between top and bottom percentiles of banks as classified by the two efficiency parametrization methods. * indicates significant difference from 25% (10%, 5%, 1%) at the 10% level (Chi-square test, two-tailed). SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$).

The interpretation of these results relies on the benchmark study of Fiordelisi (2007), which reports values around 60% for the shareholder value efficiency of European banks. Given that the orientation toward maximizing shareholder value is generally thought to be more stringently implemented in the US, it is not entirely surprising to obtain values of around 65% for the same timespan. Overall, results document an average SHVE of 75% from the GFA parametrization (Panel A), while SFA indicates an average SHVE of around 70%. Although a direct comparison between efficiency scores of European and American banks is not possible because efficiency is by definition an in-sample quantity, this does show that, on average, US banks are closer to their efficient frontier than their

European counterparts are to their frontier. This also resonates with Hughes, Lang, Mester, Moon and Pagano (2003), who find that listed US banks are approximately 80% market value efficient. The calculation of market value efficiency requires the bank to be listed, however. Yet the majority of US banks is private, which makes SHVE an important indicator of value creation efficiency in this context. As expected, the nonparametric frontier obtained from generalized frontier analysis yields somewhat greater efficiency scores. It is likely that this is because the GFA method constitutes a relaxation of the parametric and distributional assumptions imposed by SFA and thus enables a tighter fit to the data. Only GFA can account naturally for negative shareholder value efficiency. This will occur in a constellation when a bank is predicted to create positive value but in fact ends up destroying value. SFA cannot accommodate this feature and requires data manipulation to achieve nonnegative values of shareholder value prior to fitting the frontier. This is another conceptual advantage of GFA over SFA. It is also interesting to note that the GFA method provides lower variation in efficiency scores and both methods plausibly report negative skewness of efficiency scores. The greater dispersion and difference between mean and median for the SFA method suggests that this method may be providing some outlying efficiency scores. While these tests reveal that differences between SFA and GFA exist, the literature has documented far greater differences between parametric and nonparametric methods such as SFA and DEA (Huang and Wang, 2002, Bauer, Berger, Ferrier and Humphrey, 1998). Therefore SFA and GFA can be treated as methods providing compatible efficiency scores. Panel B investigates the (rank) correlations between the efficiency scores. If the efficiency parametrization methods are reasonably compatible, one would expect a positive similarity between the efficiency-based rankings of banks. In fact, the two methods do display strong and highly significant positive rank correlations, which indicates that the two methods provide compatible efficiency parametrizations. This impression is further strengthened by considering the overlap between the best and worst practitioners in the US banking industry. The rationale behind considering the overlap between the best and worst performing banks is that even if two efficiency score distributions do not align well in their totality, they can still be efficacious, for example in terms of policy implications, if they identify similar banks as being highly (in-)efficient. Therefore Panel C of Table 3.1 investigates the fraction of banks that any pair of methods simultaneously places in the best (worst) percentiles of banks. Concretely, the analysis identifies those banks that are located in the top or bottom 1st, 5th, 10th and 25th percentile of the efficiency distribution and compares the proportion of banks that overlap between any two efficiency parametrization methods. A χ^2 test subsequently tests whether the overlap is statistically significantly different from one's expectation of overlap due to chance. The overlap for quantile Q subsets of two sets A, B with M and N elements is computed as follows:

$$O = \frac{C(A_Q \cap B_Q)}{\min(M, N)}, \tag{3.29}$$

where C signifies the cardinality. Findings show that overlaps are statistically significantly greater than chance, which further strengthens the conclusion that the GFA and SFA methods provide compatible results. This shows that GFA is a suitable efficiency estimation method that produces valid results.

3.4.2. Validation Analysis

Having established that the shareholder value efficiency scores obtained from SFA and GFA share many statistical properties, the next step is to investigate whether the resulting efficiency scores also align with the observed facts of the US banking industry. Hence this section analyzes the association between efficiency scores and nonfrontier indicators of performance.

Shareholder value efficiency indicates how close a given bank is to choosing an input-output mix that would enable it to create the maximum technically feasible shareholder value. Therefore it is natural to expect banks with higher SHVE to be more profitable (have a higher ROA) and to generate lower (higher) levels of cost (revenue) for a given level of value created. Higher SHVE should also be positively associated with economic value added (the measure of value creation used in this study). For further insight, I split this variable into its two components, economic profits (EP) and the capital charge, which is the product of cost of capital and lagged capital invested (see Section 2.3.2 for details). One would further expect that more shareholder value efficient banks will align positively with greater economic profits and lower capital charge. More efficient banks have been shown to possess better loan selection and monitoring skills (Chortareas, Girardone and Ventouri, 2011). Hence one can expect more SHVE banks to have lower levels of nonperforming loans. Where the capitalization of banks is concerned, there are two possible expectations: either greater efficiency can reduce equity on the expectation that future profits will offset this initial shortage (see, for example, the efficiency-risk hypothesis of Altunbas and Chakravarty (2001)); alternatively, more shareholder value efficient banks will aim to protect their valuable charter by reducing risk and will therefore hold greater amounts of equity (see, for example, the franchise value hypothesis of Berger and Bonaccorsi di Patti (2006)). A similar argument can be constructed for the fraction of liquid assets over total assets. Hence I do not formulate explicit expectations for these two variables. It has been shown that the production technology of banks may differ by size, for example due to economies of scale or relationship lending (Berger, Miller, Petersen, Rajan and Stein, 2005). Hence this section investigates the results of the validation analysis for the full sample as well as for subsamples split by bank size. Specifically, I rerun the parametrization of the shareholder value efficiency frontier for each subsample and investigate the respective correlations for each subsample separately. The strong asymmetry in bank size across the US banking industry (see Feng and Serletis, 2009) suggests that the sample be split, for example, at the 50th and 90th percentiles. Table 3.2 reports the main findings of this analysis.

The full sample results are reported in Panel A. In particular, findings show that both methods provide efficiency scores that align well with nonfrontier bank characteristics for the full sample. Thus the efficiency scores capture the majority of the expected relations. Specifically, more shareholder value efficient banks are more profitable (ROA), have lower cost ($\frac{Total\ Cost}{Total\ Assets}$) and greater revenue ($\frac{Total\ Revenue}{Total\ Assets}$), higher shareholder value creation ($\frac{EVA}{Total\ Assets}$) and a better quality loan portfolio ($\frac{Nonperf.\ Loans}{Total\ Loans}$). These banks produce both greater economic profits ($\frac{EP}{Total\ Assets}$) and lower capital charges ($\frac{Capital\ Charge}{Total\ Assets}$). The SFA and GFA methods disagree on the association between shareholder value efficiency and capitalization ($\frac{Equity}{Total\ Assets}$). While SFA associates more shareholder value efficient banks with less equity and fewer liquid assets ($\frac{Liquid\ Assets}{Total\ Assets}$), the GFA efficiency scores exhibit the opposite relation. Both explanations are plausible given the findings in the literature. Concretely, it appears that the GFA efficiency scores are capturing the benefits gained from risk aversion and preservation of a valuable bank charter, while the SFA scores reflect a more aggressive banking strategy. More importantly, however, the two methods agree on a majority of the relations. This further strengthens the conclusion that the GFA and SFA methods are generally compatible, albeit with distinct information content.

Next, I discuss the results for the split sample analysis (Panels B-D). These are obtained by estimating a separate frontier for each subsample of banks, based on the conjecture that size might be driving significant technological differences between banks. Results show, across subsamples and methods, that higher SHVE banks are more profitable, have lower cost and greater revenue per unit assets, and produce greater economic profits and EVA. They also generate a lower capital charge, although for medium and large banks only GFA is significant here. They further appear to hold less risky loan portfolios; again for large banks only GFA is significant. Furthermore, higher SHVE banks seem to reduce equity holdings (only GFA is significant for small and medium

Table 3.2.: Correlation of Bank Shareholder Value Efficiency with Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the population split by size into the smallest 50%, the medium 40% and the largest 10% of banks. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A: All Banks		*Panel B: Small Banks* (0-50%)		*Panel C: Medium Banks* (50-90%)		*Panel D: Large Banks* (90-100%)	
Correlates	E[sgn]	**SFA**	**GFA**	**SFA**	**GFA**	**SFA**	**GFA**	**SFA**	**GFA**
ROA	+	0.2788***	0.1194**	0.3122***	0.3195***	0.3791***	0.2887***	0.2694***	0.2427**
$\frac{Total\ Cost}{Total\ Assets}$	−	-0.0005*	-0.0795**	-0.1153**	-0.0983*	-0.0055	-0.1100	0.0144	-0.0452
$\frac{Total\ Revenue}{Total\ Assets}$	+	0.1344**	0.0544***	0.0396*	0.0899	0.0490	0.0603**	0.0761	0.0765
$\frac{Equity}{Total\ Assets}$	±	-0.0998*	0.0199*	0.0246	-0.1873**	-0.0335	-0.1538*	-0.0438	-0.1425
$\frac{EVA}{Total\ Assets}$	+	0.4911**	0.1985***	0.4810***	0.6766***	0.7245***	0.6143***	0.5574***	0.6287***
$\frac{EP}{Total\ Assets}$	+	0.4943***	0.2295***	0.5131***	0.6142***	0.7554***	0.5438***	0.5297***	0.4479***
$\frac{Capital\ Charge}{Total\ Assets}$	−	-0.2959**	-0.6441***	-0.1523***	-0.3575***	-0.1344	-0.1996***	-0.0764	-0.3248*
$\frac{Liquid\ Assets}{Total\ Assets}$	±	-0.0367**	0.0486*	0.0151	0.0040*	0.0110	-0.0638*	-0.0316	-0.0930
$\frac{Nonperf.\ Loans}{Total\ Loans}$	−	-0.0563**	-0.0888**	-0.0626**	-0.1046**	-0.0979**	-0.1406*	-0.0560	-0.1131*

banks). While small banks appear to favor liquid assets, medium banks slightly reduce this balance sheet position. Again this is indicated only by GFA.

Overall, the validation analysis reveals that both SFA and GFA shareholder value efficiency scores are associated in plausible ways with other nonfrontier measures of bank performance. More shareholder value efficient banks appear to accomplish this efficiency by a strong focus on loan portfolio quality and profitability. Both cost minimization and revenue maximization are beneficial for value creation in these banks. These findings are largely independent of bank size. I also find that, probably due to the greater flexibility of the GFA method, the efficiency scores derived from this parametrization are more informative than those derived from SFA, judging by the greater frequency of significant rank correlations.

3.4.3. Regression Analysis

This section investigates the explanatory contribution and economic relevance of shareholder value efficiency to the analysis of value creation in US banks. To this end I formulate the following baseline model:

$$\frac{EVA_{i,t}}{C_{i,t-1}} = \alpha + \beta\psi - \text{eff}_{SFA,i,t} + \gamma\psi - \text{eff}_{GFA,i,t} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{16}\theta_t d_t + \upsilon_i + \epsilon_{i,t}. \quad (3.30)$$

Here $\psi - \text{eff}_{m,i,t}$ is shareholder value efficiency estimated by the method m for $m \in \{SFA, GFA\}$. d_t are time dummies, υ is a firm fixed effect and ϵ is the disturbance. Standard errors are clustered by banks. Further specifications add cost efficiency ($x - \text{eff}_{m,i,t}$) and revenue efficiency ($\tau - \text{eff}_{m,i,t}$). This analysis also investigates the importance of managerial ability (MA) for bank value creation. In so doing, I follow the method of Demerjian, Lev and McVay (2012), which is explained at length in Chapter 5. To purge variation not due to the influence of efficiency I also add control variables ($\mathbf{z}$), which include ROA, the log of gross total assets ($BKSIZE$), the ratio of nonperforming loans to total loans (NPL) and the leverage ($LEVRAG$) of the bank.[6] The dependent variable is economic value added scaled by lagged capital invested, to reflect the flow nature of value creation. The use of lagged capital invested reduces the sample to 106,564 bank-year observations.

The results of this analysis are reported in Table 3.3. The various specifications ex-

[6]Multicollinearity of regressors is not problematic in this dataset. Thus the greatest correlation of around 0.6 occurs between the cost and revenue efficiency measures and their lags. These lags are included in regressions that are reported in the appendix (Section A.2.3.2) without qualitatively affecting the main results.

plore the explanatory contribution of SHVE estimated by GFA and SFA. The specific questions are threefold. First, I ask whether the SHVE scores of one method subsume the information conveyed by the SHVE scores estimated by the other method (Specifications 1-6). Second, Specifications 7-10 also examine whether SHVE contains additional information above and beyond that included in cost and revenue efficiency. Finally, Specifications 11 and 12 answer the question whether the information of SHVE might be subsumed by managerial ability. These specifications not only address a question of economic relevance but they also simultaneously mitigate endogeneity concerns arising from omitted variable problems. Tests of the fixed effects specifications against the random effects model using the Hausman (1978) test showed that the random effects approach is overwhelmingly rejected in the data. I therefore choose the fixed effects model. The following regressions obtain SHVE estimates by splitting the sample of banks by size at the 50th and 90th percentiles. A separate frontier is estimated for each subsample and the resulting efficiency scores are pooled.[7] Coefficient estimates and significances are qualitatively similar if one instead estimates the frontier over the full sample of banks. I standardize all regressors to Z-Scores in all models. This will facilitate the interpretation of the economic significance of the efficiency scores. In addition to these regressions, Table 3.4 also investigates the contribution that the efficiency scores make to the explanation of value creation.

Specifications 1-6 analyze the information content of the SHVE measures, one vis-à-vis the other. Consider first Specifications 1 and 3. These compare the economic significance of SHVE parametrized by SFA and GFA respectively. First, it is important to note that the economic importance of GFA is superior to that of SFA. Thus, the impact of a one standard deviation change in the GFA-SHVE score amounts to a change in value creation of 3.83 % of lagged capital invested, while the equivalent effect is only 2.97 % for SFA. Given that the average bank creates value on the order of 5.37 % of capital invested, a 3.83 percentage point increase is substantial. Although less extreme, the greater economic importance of GFA-SHVE holds when control variables are added to the regression in Specifications 2 and 4. Furthermore, between Specifications 1 and 3, the GFA specification exhibits a substantially greater adjusted R^2 than the SFA specification. The control variables show that more value-creating banks are more profitable (ROA), more highly leveraged ($LEVRAG$) and larger ($BKSIZE$). Moreover, these banks have a weak preference for higher quality loan portfolios (NPL).

[7] This is in line with a number of studies that estimate bank technologies that vary according to different characteristics such as for example McAllister and McManus (1993) and Feng and Serletis (2009) for size or Mester (1993) for type of ownership structure.

Table 3.3.: Regression Analysis of Shareholder Value Efficiency.

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi - \text{eff}$) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency respectively. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are Z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA}$	0.0297***	0.0180***			0.0211***	0.0160***	0.0295***	0.0175***			0.0161***	0.0221***
	(44.48)	(28.11)			(29.50)	(26.06)	(44.04)	(26.80)			(26.18)	(31.13)
$\psi - \text{eff}_{GFA}$			0.0383***	0.0193***	0.0337***	0.0175***			0.0390***	0.0201***	0.0176***	0.0314***
			(20.87)	(15.17)	(20.14)	(15.45)			(20.32)	(14.89)	(15.71)	(19.72)
$x - \text{eff}_{SFA}$							-0.00195***	-0.00366***				
							(-2.79)	(-6.00)				
$\tau - \text{eff}_{SFA}$							0.00291***	-0.0000859				
							(6.62)	(-0.25)				
$x - \text{eff}_{GFA}$									-0.00536***	-0.00465***		
									(-8.77)	(-10.42)		
$\tau - \text{eff}_{GFA}$									0.000991**	0.00217***		
									(2.44)	(5.89)		
MA											0.00359***	0.00427***
											(10.94)	(11.35)
ROA		0.0471***		0.0414***		0.0376***		0.0473***		0.0412***	0.0375***	
		(52.65)		(35.80)		(33.42)		(52.29)		(35.08)	(33.44)	
NPL		-0.00120*		-0.000837		-0.00120*		-0.00120*		-0.000957	-0.00123*	-0.0109***
		(-1.66)		(-1.16)		(-1.70)		(-1.66)		(-1.33)	(-1.75)	(-15.74)
$BKSIZE$		0.0247***		0.0148***		0.0237***		0.0238***		0.0159***	0.0251***	0.0301***
		(8.52)		(5.13)		(8.22)		(8.12)		(5.59)	(8.60)	(9.78)
$LEVRAG$		0.0259***		0.0236***		0.0224***		0.0261***		0.0239***	0.0221***	0.0123***
		(36.87)		(33.09)		(31.90)		(36.79)		(33.33)	(31.42)	(18.30)
Constant	0.0283***	0.0548***	-0.000333	0.0657***	-0.0147***	0.0516***	-0.0390***	-0.00170	0.00141	0.0191***	0.0510***	-0.0147***
	(24.51)	(37.65)	(-0.25)	(48.96)	(-10.16)	(34.98)	(-27.74)	(-1.17)	(0.98)	(13.90)	(34.26)	(-9.24)
Adj. R^2	0.418	0.583	0.485	0.586	0.518	0.604	0.419	0.584	0.487	0.588	0.605	0.540
N	106564	106564	106564	106564	106564	106564	106564	106564	106564	106564	106564	106564

These results align with the main findings from the validation analysis. Specifications 5 and 6 include SFA and GFA-SHVE jointly, both with and without control variables. GFA-SHVE is again more economically significant in both cases. Specifically, when GFA and SFA are jointly included in the regression, the t-statistic for the SFA-SHVE nearly halves and the coefficient decreases from 0.0297 to 0.0211 vis-à-vis Specification 1. On the other hand, the decrease in the GFA coefficient is only from 0.0383 to 0.0337, with the t-statistic virtually unchanged. However, including both SHVE measures provides a significant increase of the adjusted R^2 which, along with the fact that both SHVE parametrizations maintain their significance, confirms the conclusion from the validation analysis, namely that the two SHVE measures contain similar but distinct information sets, with GFA being the more informative measure.

Next, I turn to the analysis of Specifications 7-10. These investigate whether SHVE makes a meaningful contribution to the explanation of value creation above and beyond the contribution of cost and revenue efficiency. In economic terms, the question is whether being cost or revenue efficient is a sufficient condition for value creation. All four specifications show that cost efficiency tends to have a negative impact on value creation, while revenue efficiency is weakly positive. This is the case regardless of whether cost and revenue efficiency are parametrized using SFA or GFA.[8] A reasonable explanation for this finding could run as follows. Cost efficiency gains are likely to require restructuring initiatives that, at least initially, tend to cause frictions and may destroy value. Consider for example initial organizational difficulties after staff have been laid off. The organizational adjustments inevitably cause a loss of value at the outset, while the leaner structure may be beneficial in the long run.[9] Unsurprisingly, the coefficient on revenue efficiency is positive as it likely entails an expansion of economic activity and may, for example, subsume beneficial scale effects. Again, results show that the economic significance of the GFA-SHVE scores is greater than that of the SFA scores. In addition, the inclusion of cost and revenue efficiency into the regression provides only a marginal increase in adjusted R^2, which suggests that SHVE is an important value driver, while cost and revenue efficiency cannot be viewed as sufficient for value creation.

A main source of doubt about the validity of regression analyses is the potential

[8]This documents the ability of GFA to measure efficiency scores other than SHVE, which is further supported by findings regarding cost efficiency in Appendix A.3. In further (unreported) analyses I rerun Specifications 9 and 10 using SFA to parametrize cost and revenue efficiency, with qualitatively unchanged results.

[9]The specifications including lags of cost efficiency in Appendix A.2.3.2 support this interpretation. The lags are found to be positively significant for value creation.

for endogeneity. Specifically, it is conceivable that both shareholder value creation and shareholder value efficiency are highly correlated with an unobserved third factor, the influence of which has not been filtered out by the other control variables in the regression.[10] A prime candidate for such an omitted factor would be managerial ability (MA). Hence I include a proxy of managerial ability in Specifications 11 and 12. The ability of management to influence the performance of firms has been shown to be substantial (Beatty and Liao, 2011, Bertrand and Schoar, 2003). Demerjian, Lev and McVay (2012) argue that a key function of management is to maximize revenue in an efficient manner. However, the revenue efficiency of a bank will depend on more than just the activities of management. Therefore one should purge revenue efficiency scores of bank-specific effects and use the resulting residual as the indicator of managerial ability. The authors use data envelopment analysis (DEA) to obtain revenue efficiency scores and purge these of bank-specific effects by Tobit-regressing them on a set of controls.[11] Therefore I compute this measure of managerial ability and include it in the regression specifications.

In addition to making inference more robust to the influence of endogeneity, this approach will allow insight into the importance of bank managers for value creation. That is, I examine whether SHVE is an important driver of value creation or whether its impact is fully subsumed by the ability of management. One could argue that it is a central task of managers to maximize the creation of value on the behalf of owners. In this case one should expect managerial ability to be positively related to value creation. However, managerial ability may not be an adequate indicator of value creation. Factors that make this case more likely include asymmetric effects of local market heterogeneity on banks and their managers or adverse effects such as empire building, agency problems or earnings management, which have been sufficiently documented in the literature (Jensen and Meckling, 1976, Hughes, Lang, Mester, Moon and Pagano, 2003, Shen and Chih, 2005). In this case I expect SHVE to retain its significance and sign and to contribute more to the explanation of value creation than managerial ability.

Specification 11 shows that, as expected, managerial ability is positively and highly significantly associated with value creation. Its impact, however, is not very economically significant, judging by the magnitude of the coefficients relative to those of the

[10] Alternatively, reverse causation might be influencing results if being more shareholder value efficient entails greater value creation and greater value creation can lead to higher shareholder value efficiency. However, this source of endogeneity is not as troubling in the present context as the analysis does not claim to establish causation.

[11] Cantrell (2013) has shown that this measure is an efficacious indicator of managerial ability in banks. For further details on the construction of the MA variable see Chapter 5.

Table 3.4.: Contribution of Efficiency Measures to Adjusted R^2 in % of Adjusted R^2.

This table reports the contribution to adjusted R^2 made by each variable in the regressions in Table 3.3. Specifically, each cell indicates how much the regressor contributes to the explanatory power of the regression indicated by the column heading. The contribution to adjusted R^2 was computed as $C_j = \frac{R^2 - R_j^2}{R^2}$, where C_j is the contribution of the j$^{\text{th}}$ variable, R_j^2 is the adjusted R^2 computed without that variable and R^2 is the total adjusted R^2. $\psi-$eff represents shareholder value efficiency, while $x-$ eff and $\tau-$ eff indicate cost and revenue efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012).

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA}$	16.5	3.9			6.3	2.9	16.0	3.6			3.0	6.5
$\psi-\text{eff}_{GFA}$			28.1	4.4	19.3	3.4			28.3	4.6	3.5	15.5
$x-\text{eff}_{SFA}$							0.1	0.2				
$\tau-\text{eff}_{SFA}$							0.1	0.0				
$x-\text{eff}_{GFA}$									0.4	0.2		
$\tau-\text{eff}_{GFA}$									0.0	0.1		
MA											0.1	0.2

SHVE scores. Moreover, both the SFA- and GFA-based SHVE scores maintain the signs and significances that were observed in the main analysis. This shows that endogeneity arising from omitted variables is not driving the main results. More importantly, these results also show that SHVE scores are important in explaining the creation of value in US banks in their own right. Furthermore, this points to the existence of some of the problems mentioned above. I leave disentangling the precise reasons for this finding to future research as a thoroughgoing investigation of this question is beyond the scope of this thesis. It has been argued in the literature (Beatty and Liao, 2011) that ROA can proxy for managerial ability. To alleviate the concern that this effect may be driving the low economic significance of MA in Specification 11, Specification 12 reruns the regression without ROA. While the coefficient on MA does increase somewhat, it is still far smaller than that of the SHVE measures, which supports the initial interpretation.

The final step of the regression analysis focuses on the explanatory contribution of the SHVE measures, vis-à-vis one another and vis-à-vis cost and revenue efficiency as well as managerial ability. It could be that even though less economically significant, SFA-SHVE is a statistically more informative variable in explaining value creation. To explore this question, I re-estimate each of the models above various times. Each run omits one efficiency score and records the change in adjusted R^2 resulting from adding a particular efficiency score. The percentage change in adjusted R^2 is reported in Table 3.4. The column headers identify the Specification from Table 3.3 that is being considered as the benchmark.

Given that these regressions include fixed time and bank effects, the contributions to adjusted R^2 made by the shareholder value efficiency scores are substantial. Thus, including SHVE parametrized by GFA into a model that has only fixed effects contributes 28.1% to adjusted R^2 (Specification 3). The comparable contribution of SFA is lower but still a sizeable 16.5%. Control variables dampen the explanatory contribution of the SHVE scores but cannot eliminate it, as is shown in Specifications 2 and 4. In all cases, the GFA-SHVE scores are more informative than those obtained from SFA. This is supported by Specification 5, which includes both SHVE measures. Here GFA-SHVE contributes 19.3% to the adjusted R^2, while the SFA counterpart only delivers 6.3%. Interestingly, the contribution to the explanation of value creation provided by cost and revenue efficiency is vanishingly small (Specifications 7-10). Although slightly greater contributions of the GFA cost efficiency scores suggest that the greater information content for the GFA efficiency scores might hold not only for SHVE but also for cost and revenue efficiency scores, I do not overemphasize this result. Finally, Specification 11 shows that managerial ability is almost irrelevant to explaining value creation in the presence of SHVE. This is in line with findings from the preceding analysis, where MA is found to be economically only marginally significant. This finding holds even when ROA is excluded from the regression (Specification 12). As before, GFA is the more meaningful out of the two SHVE variables in these two Specifications (11, 12).

In sum, I conduct a number of analyses which establish that GFA is a suitable method for the estimation of efficiency scores. These analyses show that it is both more economically significant and more informative in this respect than equivalent efficiency scores obtained from SFA. They further demonstrate that SHVE is an important concept that cannot be simply subsumed under cost and revenue efficiency or managerial ability.

3.5. Robustness Checks

In order to ensure that this analysis is providing valid and reliable results, I carry out a number of robustness checks, the majority of which are reported in Appendix A. First, to check that the SHVE scores themselves are not spurious, I calculate the correlation of the efficiency scores in period t and all periods $t+1$ until T. One would expect to observe positive correlations that decrease over time, since efficiency is likely to be a bank characteristic that changes only slowly. Unreported results find precisely this pattern for both SFA and GFA.

Second, as regards the validation analysis discussed in Section 3.4.2, I rerun the analysis for a balanced sample of banks. Results are qualitatively unchanged. I also rerun the analysis for nonfrontier performance measures shifted one period into the future; in other words, this robustness check examines the capacity of SHVE scores to predict nonfrontier performance characteristics of banks. As before, results show that both SFA and GFA provide meaningful and plausible predictions. A similar, unreported, check also investigates the relation between SHVE and nonfrontier performance multiple periods into the future and finds that the dynamic patterns displayed by the rank correlations of nonfrontier performance indicators both with the SFA- and GFA-SHVE measures are remarkably similar. Another robustness check further considers the correlation of the long-sectional average of SHVE scores with the long-sectional average of bank nonfrontier characteristics. Again the results show highly significant and plausible correlations for both SFA and GFA.

Third, the main analysis uses the standard definition of managerial ability proposed by Demerjian, Lev and McVay (2012). In order to assure the robustness of the key results, I modify this definition by using SFA instead of DEA to compute the revenue efficiency measure that serves as a basis for the MA proxy (see Section A.2.3.3). Moreover, I explore a yearly specification for MA instead of a pooled cross-sectional one (unreported). Additionally, I also change the set of control variables used in the first-stage regressions to purge the revenue efficiency scores from bank-specific factors (unreported). The main results continue to hold. Furthermore, I re-estimate the specifications in Table 3.3, including lags of the efficiency scores and of managerial ability, because one might argue that efficiency takes time to influence value creation. Again, results are qualitatively unchanged (see Section A.2.3.2). Moreover, to address possible endogeneity concerns, I rerun the regression analysis using lagged SHVE only. Again, results are qualitatively unchanged. Finally, to investigate the ability of GFA to parametrize efficiency scores other than SHVE, Section A.3 carries out the statistical and validation analyses with attendant robustness checks for cost efficiency. These analyses confirm the complementary nature of SFA and GFA.

3.6. Conclusion

This chapter develops and investigates a novel method, generalized frontier analysis, for the estimation of economic and technological frontiers. This method is nonparametric and stochastic and hence combines the advantages of previous approaches without inheriting their limitations. I apply this method to the shareholder value efficiency of a large sample of US commercial banks.

Results document that both the SFA and the GFA methods provide efficiency scores that have plausible distributional characteristics. This validates GFA as an efficiency measurement method. Furthermore, the findings show that the efficiency scores from GFA align with other nonfrontier indicators of bank performance. In particular, I find relations between these nonfrontier performance measures and SHVE that conform with reasonable priors derived from the literature. More importantly, however, considering a sample split by bank size shows that GFA provides efficiency scores that contain at least as much information about bank performance as equivalent SFA-based scores. This further corroborates the capacity of GFA to parametrize efficient frontiers.

Moreover, SHVE scores derived from GFA have a greater economic significance in explaining the value creation of US banks than similar scores derived from SFA. This also holds when managerial ability is included in the analysis, which implies that SHVE is an important driver of value creation in its own right and not simply a proxy for the ability of management. Managerial ability is in turn found to be a statistically significant but economically marginal driver of bank value creation. Furthermore, I find the economic and statistical significance of cost and revenue efficiency to be equally negligible compared to SHVE. This confirms that cost and revenue efficiency are not sufficient for the creation of value. These results are robust to a wide variety of robustness checks.

This analysis confirms that shareholder value efficiency can be parametrized by way of GFA and that it is a meaningful concept that can make a contribution to the understanding of bank value creation. While results show that managerial ability is an important variable that influences value creation in banks, it would be of interest to investigate through which channels managerial ability is able to do so, why its impact is lower than that of SHVE and why it does not subsume the information in the SHVE scores completely.

4. Bank Transparency, too Much of a Good Thing?

Banks are believed to be opaque to outsiders by virtue of the assets that they hold. A social planner would like banks to be transparent, riskless and highly efficient intermediators of liquidity. However, these goals appear to be conflicting ones. Whether and how opacity, fragility and intermediation quality are connected is an important question of relevance to regulators, investors and the general public. Furthermore, the theoretical literature makes three conflicting predictions about this relation. To disentangle the competing theories, this chapter conceptualizes a measure of intermediation quality that overcomes important econometric challenges. It tests the resulting conjectures on a large sample of US banks and finds that intermediation quality is positively associated with opacity and fragility. These results imply that demanding full disclosure and transparency from banks may bring with it negative externalities in terms of intermediation quality that policymakers may wish to take into account.

4.1. Introduction

How banks create liquidity, i.e. how they intermediate between borrowers and lenders is a question of the greatest interest. After all, real economic activity is critically dependent on the free flow of funds and provision of credit. One reason for the recent shortage of loan provision in the UK (see for example Jenkins and Jones, 2012, O'Donnell, 2012) may lie with overly zealous regulation in the wake of the financial crisis. In fact, the resulting unwillingness of banks to lend has triggered government intervention in a direction opposite to the initially restrictive capital requirements. Banks have been offered governmental subsidies to encourage more tightly regulated banks to lend more (for a popular discussion of the funding for lending scheme see for example Nixon, 2013). Society and regulators care primarily about the availability of credit and less risky, more transparent banks. These two goals may be conflicting ones however. Thus it is conceivable that a certain degree of risk-taking respectively in-transparency on the part of banks is desirable or even necessary for financial intermediation. Three strands of the theoretical literature make conflicting predictions with respect to the role of bank transparency and fragility in the context of bank intermediation (e.g. Dewatripont and Maskin, 1995, Diamond and Dybvig, 1983, Myers and Rajan, 1998, Diamond and Rajan, 2000, Coval and Thakor, 2005). Whether there is any social cost to bank transparency in terms of the intermediation quality provided by banks is therefore an empirical question of both theoretical and practical relevance. I proceed to disentangle these theories and thus shed some light on this question.

While there is growing evidence to suggest that banks are in fact opaque (see e.g. Morgan, 2002, Jones, Lee and Yeager, 2012, Flannery, Kwan and Nimalendran, 2013), it remains an open question whether this is desirable and, if not, whether this can be changed. Some authors suggest that opacity is inherent to the functioning of banks by virtue of the nature of the assets that they hold (consider for example Morgan, 2002, Berger and Bonaccorsi di Patti, 2006). On this reading, opacity may not be avoidable without incurring prohibitively high information cost and therefore ought to be tolerated. A more critical viewpoint is taken by research that suggests that insufficient transparency of counterparties may cause credit chains to break down, which would ultimately hamper the liquidity supply to the economy (Pritsker, 2010). Also, Dwyer and Tkac (2009) argue that the turmoil of the recent financial crisis may partly have arisen due the to insufficient transparency of novel securitized financial products that were being created and traded. Furthermore, opacity may induce information congestion such that bad news gets initially delayed by management and is then suddenly and rapidly revealed in the wake of shocks (Balboa, López-Espinosa and Rubia, 2013). Finally Jones, Lee and Yeager (2012) claim that bank opacity fosters collusion, price manipulation, contagion and excessive risk-taking. Taken together this is powerful evidence to suggest that opacity is negative for financial markets as a whole. Curiously, Thakor (2005) points out that the Federal Reserve has taken a reserved stance towards increased disclosure requirements for banks. Given the criticism of opacity voiced in the literature, this lenient approach can prima facie not be justified.

The view, that both opacity and fragility are detrimental to the quality of financial intermediation, is formalized by Coval and Thakor (2005), who claim that opaque and obviously fragile banks are unable to act as intermediaries between pessimistic depositors and optimistic entrepreneurs. For reasons that will become apparent later, I call this hypothesis "Opacity-Ownership Hypothesis". On the other hand the theories of Diamond and Rajan (2000) and Diamond and Rajan (2001) suggest that both fragility and opacity will be beneficial for intermediation due to the disciplining effects that fragility has on bank managers. I investigate this theory under the “Opacity-Fragility Hypothesis”. In a third strand of the literature Dewatripont and Maskin (1995) and Berglöf and Roland (1997) show that, while fragility may impede intermediation quality due to softer budget constraints, opacity may, in fact, be beneficial due to the disciplining effect that it has on borrower firms. From this literature I develop the “Opacity-Hardness Hypothesis”. These three strands of the literature allow for different predictions about the roles of opacity and fragility in the context of financial intermediation. Ongoing theoretical work that explicitly accounts for opacity in banks has unfortunately not progressed sufficiently to be empirically testable.[1]

This chapter operationalizes the above predictions and takes them to the data. Specifically, it investigates the link between the opacity, fragility and intermediation quality of banks on a large dataset of US banking data spanning the years 1994-2010 and containing 118.164 bank-year observations. Intermediation quality is defined as the efficiency of banks in terms of liquidity creation relative to their peers. To test these alternative hypotheses the analysis proceeds in two steps. First, it uses stochastic frontier analysis and generalized frontier analysis together with the liquidity creation measures of Berger and Bouwman (2009) to parametrize a stochastic frontier. The resulting liquidity efficiency score subsequently proxies for intermediation quality. This approach is necessary because econometric problems, to be elaborated later, preclude the direct study of the relation between liquidity creation and both opacity and fragility. Second, I regress this measure of intermediation quality on a number of control variables and various balance sheet indicators of opacity and fragility. These regressions provide support for the “Opacity-Fragility Hypothesis” which posits that both the fragility and opacity of banks will exert a positive effect on intermediation quality. This indicates that bank opacity has important positive externalities. Both opacity and fragility are independent of the level of fragility exhibited in the data but depend on the level of opacity. This indicates that opacity can be viewed as distinct from but functionally similar to fragility from the viewpoint of both depositors and banks as postulated by the theory. I carry

[1] Monnet and Quintin (2013) have begun developing an explicit model in which delegation of decisions to informationally opaque agents (e.g. banks) is ex ante optimal for all other agents in the economy. However, the authors themselves label their analysis as “very preliminary and incomplete”. While a more direct theoretical justification of the present hypotheses would be valuable, their work is as yet not complete. So far, their advances only allow a prediction about opacity, while their work remains silent on the role of fragility. As will subsequently be shown, the theoretical literature provides reasons to suppose that both these factors are at play. Therefore I base my analysis on this body of research rather than invoking the very promising but unfortunately unfinished work of Monnet and Quintin (2013).

out a large number of robustness tests, which are reported in Appendix B, and find results to be stable.

The results of this chapter yield important directions for future research and policy implications of note. First, models describing the process of financial intermediation would do well to explicitly incorporate the effect of opacity in their framework. Second, policy makers need to take into account the beneficial effects that opacity has on borrower behavior. Specifically, if a regulator wishes to preserve efficient intermediation while increasing the safety of the financial system, making banks fully transparent may eliminate positive externalities and thus produce an unanticipated social cost in terms of a loss of intermediation quality. Thus, if a regulator wishes for more information on banks' operations, this additional disclosure should not be made publicly accessible.

The rest of this chapter is organized as follows. Section 4.2 deduces the main hypotheses from the literature. Section 4.3 discusses the selection of data and variables used to capture intermediation quality, opacity and fragility. Section 4.4 presents the main findings and additional analyses are discussed in Section 4.5. Robustness checks are discussed in Section 4.6. Section 4.7 concludes.

4.2. Theory and Hypotheses

This section reviews some theoretical literature related to the intermediation behavior of banks and develops the main hypotheses underlying the remainder of this chapter. First, Section 4.2.1 discusses the role of opacity and fragility in the context of budget constraints. Second, Section 4.2.2 provides a brief summary of the literature which leads to the expectation that opacity and fragility should enhance intermediation behavior. Finally, Section 4.2.3 uses the literature on agents' beliefs to deduce a third set of predictions about the role of opacity and fragility in the context of intermediation behavior.

4.2.1. Soft Budget Constraints and Opacity

I turn my attention first to the "soft budget constraint" literature. Consider for example Dewatripont and Maskin (1995). These authors formulate a model in which banks have ex ante incomplete information about the quality of borrowers. Different equilibria, differing primarily by the size of banks that exist, can arise. They find that, when both small and large banks coexist in the economy, constellations favoring the "evergreening" of debt can arise. This practice refers to rolling over loans to debtors who are technically insolvent instead of pressing bankruptcy proceedings. In this model banks do so in the hope of recovering a greater part of their initial investment if the debt is rolled over. The authors then go on to show that it may be optimal for banks to grant this refinancing, in effect imposing only soft budget constraints on borrowers, in order to recoup some of the sunk costs invested into the respective entrepreneur. A similar model is developed by Berglöf and Roland (1997), who find that budget constraints are usually harder for large banks because of the fixed costs associated with screening loans. Their model is similar to Dewatripont and Maskin (1995). However, here banks can expend effort in monitoring. Banks face a supply of projects, a fixed fraction of which are good, the rest being poor. Poor projects can succeed without requiring refinancing if the entrepreneur expends effort, which is of course the preferred outcome for a bank. If they do not succeed, these projects require refinancing after the first period. It is lucrative for the bank to refinance such projects because the recovery value relative to the overall investment will increase. The authors find that budget constraints imposed on firms by banks are harder when available new projects are better, when fixed costs of monitoring are lower and when liquidation values of assets are greater. In addition, it is natural to suppose that entrepreneurs will exert greater effort if these characteristics of the loan market and the bank are unknown to them in order to avoid the loss of their project. Hence, in other words, opacity stimulates effort, while transparency stimulates shirking. These two behavioral traits of borrowers govern the outcome of projects and hence the quality of the bank's loan portfolio and thus ultimately its fragility. Figure 4.1 provides one possible visualization of this mechanism. The bank creates liquidity, primarily through loans, but loans also leave the bank open to fragility. This is specifically the case if borrowers shirk on their projects.

In this type of model, opacity works in two ways to increase the intermediation quality of banks. First, because banks are opaque to outsiders, borrowers do not know exactly what the quality of alternative projects available to the banks is. If it is high, there is a danger that the entrepreneur's project will not be refinanced after the first period if he shirks on his effort. In this respect opacity of banks motivates existing borrowers to expend greater effort on their projects. Thus opacity increases the quality of financed projects and decreases otherwise necessary write-downs. Opacity also increases funds available for new lending if the bank normally would have rolled over a bad loan, because this practice would have frozen up assets. The second channel is related to the liquidation skill of banks and works in much the same way. If banks are opaque, it is difficult for outsiders to know whether they have high or low liquidation costs and whether they have any skill in extracting a nonzero liquidation value from firm assets.

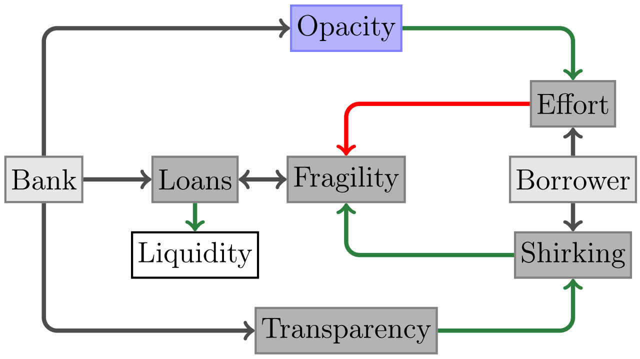

Figure 4.1.:
Liquidity-Opacity Relation in Berglöf and Roland (1997) and Dewatripont and Maskin (1995).

Light grey boxes symbolize actors, while dark grey ones symbolize actions or features. Black arrows connect without implying a specific relation, green arrows imply a supporting relation while red ones imply a inhibiting relation.

Thus banks' opacity exerts a disciplining effect on the management of borrower firms and serves to regulate the demand side. In effect, it creates harder budget constraints for borrowers. Taken together, these theories predict that opacity will positively influence the intermediation of banks. This first set of theories additionally predicts that banks that are more opaque will also have higher quality loan portfolios because of the ex ante natural selection and the disciplining impact on borrowers. Therefore more opaque banks will also be less fragile.

4.2.2. Fragility and Opacity as Disciplining Mechanisms

As an alternative starting point consider the theories of Diamond and Rajan (2000, 2001). They suggest that bank liquidity creation depends positively on the fragility of the bank. As banks become more fragile, they can more credibly commit to diligent monitoring of borrowers, thus securing the trust and funds of lenders. They can do so because lenders are able to run on the bank, which would cause it to lose its valuable charter. Although this model does not consider uncertainty explicitly, one might suppose that bank opacity plays an important role in this framework. As banks become more opaque to outsiders, the propensity of lenders to run on the bank will increase, holding fragility constant. In the words of Diamond and Dybvig (1983) "... anything that causes them to anticipate a run will lead to a run." (p. 410). As opacity increases, investors, being risk averse, will want to err on the side of caution and run early rather than late. But then more opaque banks, given a level of fragility measured by the expectation of the available information, should be systematically better intermediaries than more transparent banks since opacity increases the variation that is attached to that information. Formulated yet differently, the investor will form an expectation of fragility as a property of the bank. Opacity will influence the degree of confidence that the investor associates to that information and thus constitute a feature of the bank that exacerbates any kind of fragility the bank exhibits. Therefore, from the viewpoint of the bank and the depositor, opacity and fragility are functionally similar where the threat to the bank's charter is concerned. Hence, if a bank is disciplined by its fragility, an equally fragile but in addition opaque bank will a fortiori be disciplined. In this context one might argue that managers have an incentive to take measures that will make their bank become less opaque. However, they may have no practical way of going about this credibly. If banks are, for example, able and known to engage in practices such as earnings management, simply professing that one is not engaging in this practice is not going to enhance one's credibility with creditors. This will, mutatis mutandis, apply to opacity. It follows that there likely exists an irreducible impact of opacity on the intermediation quality of the bank and that this impact should work in the same direction as fragility. Figure 4.2 summarizes this reasoning schematically. Again, fragility enters banks primarily through the intermediation of loans. From the viewpoint of depositors, capitalization reduces fragility, while opacity increases it. Hence opacity and fragility increase the credibility of the screening commitment of the bank, which enables it to function as a more efficient intermediary.

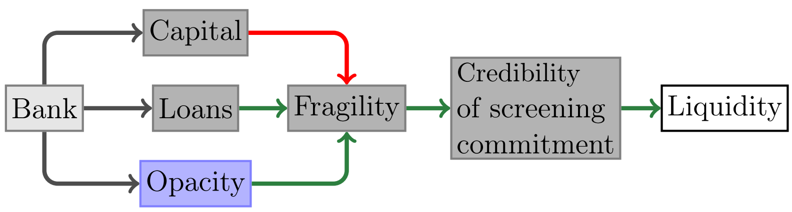

Figure 4.2.: Liquidity-Opacity Relation in Diamond and Rajan (2000, 2001).

Light grey boxes symbolize actors, while dark grey ones symbolize actions or features. Black arrows connect without implying a specific relation, green arrows imply a supporting relation while red ones imply a inhibiting relation.

4.2.3. Opacity and Agent Beliefs

Finally, consider the theory of Coval and Thakor (2005). The authors set up a model framework in which the existence of intermediaries emerges endogenously as a result of divergent opinions among agents, who are either rational, pessimistic or optimistic, which can be visualized along the lines of Figure 4.3. The optimists want to obtain funding for entrepreneurial projects from the pessimists. However, their optimism, in conjunction with the counterparty's pessimism as to the project's success, creates a gap of beliefs. This gap will be overcome if intermediaries step in and pre-commit to screening projects. Intermediaries, formed by rational agents, bridge the gap of beliefs between the pessimistic and optimistic actors and can thus channel funds from pessimists to optimists. They can credibly do so because they are composed of rational agents without a beliefs bias as to the project outcome. This enables the intermediary to design contracts where risk is distributed in accordance with the agents' beliefs; i.e. the riskiest investments are held by the most optimistic agents etc. One of the results that are of interest in the present context is a setting in which the proportion of optimists and pessimists in the population is high relative to the number of rationals. Then, if the ex ante probability of optimists' (potential entrepreneurs) being rationed is too high, intermediaries composed of optimists might arise (see Coval and Thakor, 2005, pp. 557-558). These are unable to pre-commit credibly to project screening and therefore, next to a demand side problem in the entrepreneurial credit market, a downward spiral in project quality perception might result when there is uncertainty as to the composition of the bank. This means that opacity as to the bank ownership's attitude towards risk will adversely affect the bank's ability to intermediate over time (Coval and Thakor's (2005) second period lending based on reputation). In this model framework I therefore expect a negative relation between opacity and intermediation. Moreover, because conservative capital structure can signal rationality, I expect a negative relation between fragility and intermediation.

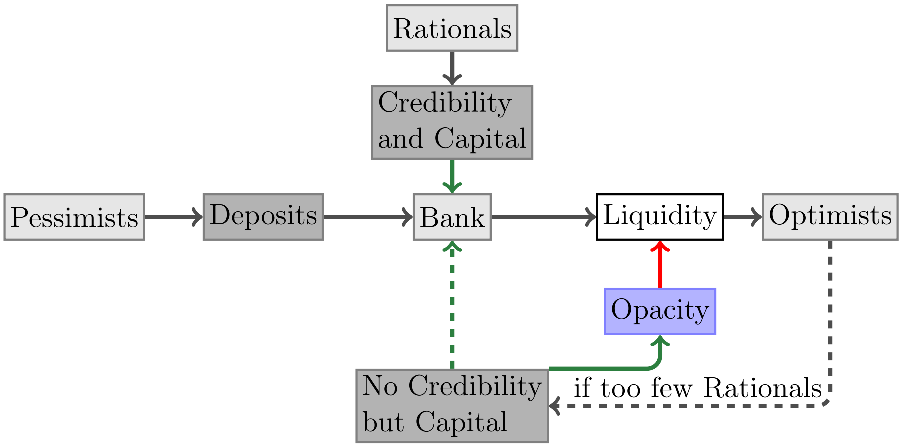

Figure 4.3.: Liquidity-Opacity Relation in Coval and Thakor (2005).

Light grey boxes symbolize actors, while dark grey ones symbolize actions or features. Black arrows connect without implying a specific relation, green arrows imply a supporting relation while red ones imply a inhibiting relation.

4.2.4. Hypotheses and Identification Strategy

Considering these three strands of the literature, it appears that the impact that opacity has on banks' intermediation quality is ultimately an empirical question. Although it is clear that none of the theories cited deals with opacity explicitly on its own, taken together each of these three bodies of literature allows for the deduction of distinct predictions about the influence that opacity will have on financial intermediation. In brief, three conflicting predictions about the relation between opacity, fragility and the quality of financial intermediation emerge.

First, the theories of Dewatripont and Maskin (1995) and Berglöf and Roland (1997) predict that better intermediaries will simultaneously be more opaque as well as less fragile. This is because entrepreneurs cannot expect that the bank will roll over their loan if they decide to shirk on their project. Thus they will exert effort, resulting in better bank loan portfolios, lower writedowns and greater intermediation quality. Second, opacity may function in a similar way as fragility in the Diamond and Rajan (2000)-setting because it exacerbates the effects of fragility. This would facilitate intermediation quality. Third, fragility and opacity, in this case about who constitutes the bank, optimists or pessimists, may inhibit liquidity creation in the Coval and Thakor (2005)-world because of distrust among the economic agents.

Thus, while the null hypothesis assumes that neither opacity nor fragility are relevant for intermediation quality, I formulate three alternative hypotheses as follows:

A1: Opacity-Hardness Hypothesis*: Higher intermediation quality banks are more* *opaque and less fragile.*

***A2: Opacity-Fragility Hypothesis**: Higher intermediation quality banks are more opaque and more fragile.*

***A3: Opacity-Ownership Hypothesis**: Higher intermediation quality banks are less opaque and less fragile.*

A1 and A2 make identical predictions about the effects of opacity but differ in their assessment of fragility, while A3 makes the opposite prediction about opacity. Thus, the following regression can distinguish whether A1 and A2 on the one hand or A3 on the other hand are supported by the data.

$$IQ_{i,t} = \alpha + \boldsymbol{\beta}'\mathbf{CONTROL}_{i,t} + \gamma OP_{i,t} + \epsilon_{i,t}. \tag{4.1}$$

Here IQ, intermediation quality, is the dependent variable. OP characterizes the bank's level of opacity. Variables that capture other variation not due to opacity are represented by the vector of control variables **CONTROL**. If A1 or A2 hold, one would expect to find a significantly positive coefficient γ. If on the other hand γ is significantly negative, A1 and A2 must be rejected in favor of A3.

The A1/A2 case can be further disentangled by investigating the influence of bank fragility on the quality of intermediation. Due to the distinct predictions that A1 and A2 make about the loan portfolio quality and thus ultimately about the fragility of the bank, it is possible to distinguish between these by investigating the impact of opacity and fragility on the quality of financial intermediation separately and jointly. Specifically, under A1 opacity should be positively related to intermediation quality, while bank fragility should be negatively related. Under A2 one would expect positive signs on both opacity and fragility.

$$IQ_{i,t} = \alpha + \boldsymbol{\beta}'\mathbf{CONTROL}_{i,t} + \gamma OP_{i,t} + \delta FRAG_{i,t} + \epsilon_{i,t}. \tag{4.2}$$

Here $FRAG$ represents the variable chosen to control for fragility. If δ is significantly positive both in regressions of the form 4.2 and with γ constrained to zero, the test will reject A1 in favor of A2. This proposed identification strategy requires the definition of a number of variables. Concretely, it requires suitable proxies for the quality of financial intermediation, for opacity and for bank fragility. These are the subject of the subsequent section.

4.3. Data and Variables

Data on US commercial banks is obtained from the December Call Reports via the Chicago Federal Reserve and additionally I collect the $CATFAT$ and $CATNONFAT$ measures of liquidity creation from Christa Bouwman's website.[2] The data cleaning procedures are as described in Section 2.3. In total the sample spans the years 1994 - 2010 and contains 118.164 bank-year observations.

In this study intermediation is measured by the ability of banks to transform more liquid liabilities into less liquid assets and many small units of deposits into fewer larger units of loans. The extent to which banks are able to do this is reflected in the overall amount of liquidity created. The recent work by Berger and Bouwman (2009) provides an operational measure of this feature of bank activity. To obtain their measures, they separate balance sheet positions into categories related to the ease and cost of liquidation and attach weights to the respective categories. The weights are chosen so as to yield maximum liquidity creation when liquid liabilities (e.g. deposits) are used to finance illiquid assets (e.g. commercial & industrial loans). Both the source of financing and the use of the funds is weighted by either $\frac{1}{2}$, 0, or $-\frac{1}{2}$ according to whether it contributes to or reduces liquidity creation. Thus liquidity creation is a weighted sum of the bank's assets. They define two such measures, one which includes off-balance-sheet items (referred to as $CATFAT$) and one which does not include this category of assets ($CATNOFAT$).[3] A more narrow precursor to these measures is the liquidity transformation gap of Deep and Schaefer (2004). However, this measure does not explicitly consider either off-balance-sheet items or the possibility of both liquidity creation and its destruction. The latter occurs if, for example, illiquid liabilities are used to finance liquid assets. Therefore the main analysis is based on the work of Berger and Bouwman (2009) and their definition of liquidity creation. However, one of the additional analyses does investigate the implications of the Deep and Schaefer (2004) measure with encouraging results.

To control for fragility, I use several measures and provide acronyms in brackets. Simple measures are leverage ($LEVRAG$) or the ratio of nonperforming loans over total loans (NPL). Furthermore, the quantity of liquid assets scaled by total assets can capture the liquidity of a bank ($LAGTA$). Additionally, the quantity of risk weighted assets scaled by total assets ($CREDRSK$) can capture how tightly a bank is financed.

---

[2] I thank Christa H. Bouwman for making her data freely available.

[3] They also discuss equivalent $MATFAT$ and $MATNONFAT$ measures. These take as the criterion for weighting assets not the category but the maturity of the assets. However, these alternative measures are not made publicly available.

Another widely used and useful measure is the Z-Score (see for example De Nicoló, 2000, De Nicoló, Bartholomew, Zaman and Zephirin, 2004). This variable measures by how many standard deviations the return on assets must fall for capital to become zero. This variable is computed in two alternative ways to mitigate data availability concerns. First, I compute the variance of return on assets using the cross sectional, yearly data ($ZIND_{pool}$). This specification captures the distance to default where the variability of returns is driven by the population of banks in a given year and thus conserves observations because this value will be available and equal for all banks. However, this is not strictly a bank-specific measure of risk. The alternative parametrization calculates Z-Score using the three year moving average of ROA for each bank where sufficient data is available ($ZIND_{MA(3)}$). This measure is bank-specific but sacrifices observations.[4] Typical alternative measures of bank fragility could be, for example, the volatility of stock returns or betas. However, these are disregarded in this analysis for practical reasons: the majority of US commercial banks are not listed, hence the dataset does not afford access to these measures (for a similar argument see Berger and Bouwman, 2009).

Opacity itself is a challenging concept to operationalize. In the literature, banks' asset structure, market microstructure properties and credit ratings have been utilized to this end. Morgan (2002) investigates the propensity of rating agencies to disagree on banks' ratings. He finds systematically higher disagreement for banks than industrials, which indicates that banks are in fact more opaque. Furthermore, the propensity to disagree on ratings is systematically related to loans, trading assets and cash. The rationale behind these associations is that loan portfolios are inherently opaque to outsiders and that trading assets and cash are easily shiftable, thus lending themselves to agency problems in the spirit of Myers and Rajan (1998). Related literature includes Jones, Lee and Yeager (2012) (henceforth JLY). They analyze the effect of bank mergers on the revaluation of rival banks. They find that more opaque banks (banks holding greater quantities of opaque assets) benefitted more from revaluations. In their study, assets are categorized into four groups. The first group contains "commercial and residential real estate loans". These are considered transparent. The second group contains "other loans", which are considered opaque. The third group contains other opaque assets and is calculated as a residual of the other three groups. Finally, the fourth group contains transparent assets (cash, federal funds sold, securities purchased under agreements to resell, guaranteed available for sale or held to maturity securities). They analyze the effect of the financial crisis on share prices of their sample banks, finding that more

[4] To mitigate the loss of observations I obtain supplementary data on ROA in 1992 and 1993.

opaque banks suffer more severe reversals while benefitting from higher intra-industry revaluations during good times. Their results indicate that their classification of assets is able to capture bank opacity. I also consider the work of Flannery, Kwan and Nimalendran (2013) (henceforth FKN). They investigate the relation between balance sheet indicators of opacity and market microstructure properties of banks. Their results illustrate the relation between certain balance sheet positions and bank opacity. Primarily premises, fixed assets, other assets etc. are found to be important. Their conclusion, which does resonate with the general literature on bank opacity, is that certain asset classes are harder for outsiders to understand. Overall, it appears that the consensus in the literature is that the balance sheet composition of banks matters for their opacity and that certain asset classes, which are more difficult for outsiders to understand than others, can signal the opacity of banks. Therefore this chapter is based on three proxies for bank opacity. Two from JLY, namely other opaque assets ($OOAJLY$) and other loans ($OLNJLY$) and one from FKN, specifically $OPQFKN$ (see also Table 4.1). As has been noted, an alternative approach to proxy for opacity would be to utilize split ratings or market microstructure data. However, since the vast majority of US commercial banks are small and unlisted, these features are unfortunately not available for the vast majority of US commercial banks.

Having discussed available measures of opacity, fragility and liquidity creation, it becomes apparent that an investigation of the relation between liquidity creation on the one hand and opacity and fragility on the other faces some econometric challenges. These arise because the main measures of bank opacity and fragility are groups of balance sheet items. However, in the liquidity creation measure of Berger and Bouwman (2009), these enter linearly as constituents of liquidity creation. This may induce naïve regressions of liquidity creation on, for example, opacity to return spurious correlations that are simply due to the way in which components of the opacity variables are weighted when computing liquidity creation. To resolve this challenge I develop a measure of intermediation *quality*. Specifically, this chapter uses stochastic frontier analysis and generalized frontier analysis to parametrize two types of liquidity frontier and thus to derive liquidity efficiency as a proxy for bank intermediation quality. The dependent variable in the frontier parametrization is the $CATFAT$ measure of liquidity creation from Berger and Bouwman (2009) and hence the resulting intermediation quality variables are labelled IQ_{SFA}^{CF} (IQ_{GFA}^{CF}). The selection of the sample, the definition of inputs and outputs as well as their respective prices follows the discussion in Section 2.3. This frontier is the boundary of the "liquidity production possibility set" spanned by all banks in the sample. Stochastic frontiers have been used to investigate many features of banks such as technical efficiency, cost, revenue and profit efficiency (see Fethi and Pasiouras, 2010, for a survey) and recently also shareholder value efficiency (Fiordelisi, 2007) and market value efficiency (Hughes, Lang, Mester, Moon and Pagano, 2003). Traditional methods for the parametrization of efficient frontiers include stochastic frontier analysis and data envelopment analysis. Since DEA requires the availability of prices that connect the inputs and outputs to the economic quantities of interest, such an approach will not be viable in the liquidity case (see for example footnote 2 in Chapter 3). SFA on the other hand imposes a functional form on the relation that it investigates. Furthermore, distributional assumptions with respect to error terms must be made. These assumptions may not be appropriate in a case like liquidity efficiency where no theory exists to guide the selection of functional form etc. Nonetheless, the main analysis relies on this method because SFA is well explored and understood. However, I investigate the importance of the assumptions that underlie SFA for the main results by simultaneously using generalized frontier analysis to parametrize liquidity efficiency (IQ^{CF}_{GFA}) since GFA is able to relax some of the possibly restrictive assumptions underlying SFA.

Isolating the impact of opacity and fragility from other confounding effects requires a set of control variables. I use a set of control variables that has been found to capture the salient features of the banking industry in the literature (see e.g. Pi and Timme, 1993, Mester, 1993, Mester, 1996, Berger and Bouwman, 2009 and Fiordelisi and Molyneux, 2010). Specifically, size ($BKSIZE$) is chosen to capture differences in banks that are due to their operational scope and access to funding markets. ROA captures features of banks relating to profitability. Cost efficiency (CE) is intended to filter out technological differences between banks related to dimensions other than the transformation of liquidity. The main analysis uses cost efficiency as parametrized by SFA but unreported results show that the main findings hold if cost efficiency is parametrized by the alternative GFA method or if this variable is omitted all together. Following Berger and Bouwman (2009), I also control for organizational characteristics such as holding company status and recent mergers and acquisitions. This is accomplished by way of dummy variables that take the value 1 if a bank is part of a multi-bank holding company ($MBHC$) or one-bank holding company ($OBHC$). Additional indicator variables control for the influence of M&A activity on bank efficiency (for a discussion of mergers and efficiency see for example Ahmad, Ariff and Skully, 2007). Specifically, MRG is set to one in the case of a merger and ACQ to 1 in case the bank was acquired during the last three years. It is further advantageous to control for local market characteristics by including the bank-level Herfindahl-Hirschmann index ($BKHHI$), the log bank-level population ($BKPOP$), population density ($BKPDNS$), percent income growth rates ($BKICHG$) as well as the market share of medium and large banks in the area ($BKMSML$). Bank-level means that the variables in question are computed for all markets in which banks hold deposits. As markets this chapter defines Metropolitan Statistical areas (MSAs) or non-MSA counties. It then uses data on the deposits held by each bank in each of these markets to calculate the relative significance of the market for the bank. Using these quotients as weights, it then computes the weighted HHI, population density etc. for each bank. More formally, assuming one of n banks, bank i, has deposits $d_{i,j}$ in market j, which is one of m markets the bank services, the market's importance for the bank is computed as:

$$w_{i,j} = \frac{d_{i,j}}{\sum\limits_{j=1}^{m} d_{i,j}}. \tag{4.3}$$

Then let the market have a characteristic c_j. To compute the value of characteristic c, which should be attached to bank i, c_i, I take the weighted average like:

$$c_i = \sum_{j=1}^{m} w_{i,j} c_j. \tag{4.4}$$

These variables capture the differences between banks that arise from their organizational form or location. Raw demographic data are obtained from the Bureau of Economic Analysis (www.bea.gov), while data on bank deposits are obtained from the Federal Deposit Insurance Corporation (www.fdic.gov).

Table 4.1 provides a summary of the variable definitions. It also gives the mean and standard deviation for the main variables used in the analysis. This data shows that among the opacity proxies, $OLNJLY$ takes up the greatest proportion of the bank's balance sheet on average. Here it is important to stress that the significance of the proxy variables for bank opacity does not actually depend on their taking up significant potions of the balance sheet. This is the case for three reasons. Firstly and most importantly, the mere presence of these variables suggests that the bank in question is opaque. This is because, as documented by FKN and JLY, these opaque assets are associated with other bank characteristics that suggest opacity. They are to be understood as indicators of the difficulty that outsiders have to understand the bank's balance sheet and strategy. Secondly, nonperforming loans are typically on the order of less than two percent of the bank's balance sheet. However, an increase to three percent would be viewed as extreme. Moreover, banks report return on assets on the order of about 1%, which is consistent with for example Berger (2003). Hence even a rather small percentage of bank assets has the potential of exerting a substantial influence on the bank's asset structure. Finally, it is clear that banks which hold regulatory capital on the order of 8-10% of assets, will find themselves in a very problematic situation if 5% of assets were to be lost. Therefore not having a clear picture of even a small portion of the bank's balance sheet can mean substantial risk. Among the fragility proxies, the two different specifications of the Z-Score show that when the full sample of banks is used to compute the variance of the return on assets, banks appear much less risky ($ZIND_{pool}$). This is plausible given the averaging out of idiosyncratic noise in the larger sample. The banks in this sample are also very cost efficient on average (CE). Moreover, the majority of banks tend to be bank holding companies ($MBHC$, $OBHC$). The demographic variables are generally in line with Berger and Bouwman (2009), especially if one takes into account the difference in time periods covered. The following section discusses the empirical results.

Table 4.1.: Definition of Variables.

In the empirical analysis, unless otherwise stated, all variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers.

Variable Name	**Variable Definition**	**Mean**	**SD**
	Opacity Variables		
$OOAJLY$	Other opaque assets (residual of total assets less transparent assets) (Jones, Lee and Yeager, 2012)	0.0498	0.0464
$OLNJLY$	Other loans (Jones, Lee and Yeager, 2012)	0.2290	0.1199
$OPQFKN$	Premises, fixed assets, investment in unconsolidated subsidiaries, intangible assets, other assets (Flannery, Kwan and Nimalendran, 2013)	0.0429	0.0220
	Fragility Variables		
$LEVRAG$	Leverage, ratio of liabilities over gross total assets	9.6336	2.7234
NPL	Nonperforming loans over total loans	0.0123	0.0159
$CREDRSK$	Ratio of risk weighted assets to gross total assets	0.5686	0.2655

Continued on next page

Table 4.1 – *Continued from previous page*

Variable Name	**Variable Definition**	**Mean**	**SD**
$LAGTA$	Liquid assets over gross total assets	0.3658	0.1460
$ZIND_{pool}$	Z-Score calculated using variance of return on assets derived from the pooled sample of banks	15.6875	5.8263
$ZIND_{MA(3)}$	Z-Score calculated using variance of return on assets derived from the last three bank-year observations	1.4439	1.9242
	Control Variables		
ROA	Return on assets	0.0098	0.0075
$BKSIZE$	Log of gross total assets	11.7406	1.2057
CE	Cost efficiency score derived from SFA	0.9285	0.0393
$MBHC$	Dummy variable, set to one if a bank is part of a multibank holding company	0.2495	0.4327
$OBHC$	Dummy variable, set to one if a bank is part of a onebank holding company	0.5490	0.4976
MRG	Dummy variable, set to one if a bank has been involved in at least one merger in the last three years	0.0002	0.0123
ACQ	Dummy variable, set to one if a bank has been acquired in the last three years	0.0650	0.2465
$BKHHI$	Weighted Herfindahl-Hirschmann index calculated using a bank's deposits in a given market as weights	0.2319	0.1484
$BKMSML$	Market share of medium and large banks faced by a bank in its markets, calculated using a bank's deposits in a given market as weights	0.4204	0.3155
$BKPDNS$	Population density of a bank's markets calculated using a bank's deposits in a given market as weights	2.9237	0.9192
$BKPOP$	Population of a bank's markets calculated using a bank's deposits in a given market as weights	12.2655	2.3451
$BKICHG$	Income change of a bank's markets calculated using a bank's deposits in a given market as weights	0.0484	0.0420

4.4. Empirical Results

In order to understand the relations between opacity, fragility and intermediation quality and to disentangle the three competing hypotheses, four main steps are required. In the first instance, correlations between opacity, fragility and intermediation quality provide a first look at the data. Subsequently, regressions of intermediation quality on a set of explanatory variables help to understand the impact of various balance sheet variables on intermediation quality. This will explore the way in which various aspects of bank behavior are related to intermediation quality and provide a basis for further exploring opacity in the context of intermediation quality. The second step will add the variables proxying for OP to the regression and thus examine whether there is any relation between opacity and liquidity creation. The sign of the coefficient γ in Equation 4.1 will determine the acceptance or rejection of A1/A2 on the one hand and A3 on the other. As a third step I analyze the relation between intermediation quality and fragility. This amounts to removing OP from Equation 4.1 and substituting for it $FRAG$. This step is necessary so as to understand the effects, if any, that emanate from fragility in the context of intermediation quality and to ensure that results related to opacity are stable and not merely driven by fragility. This is the first step needed to disentangle A1 and A2 by way of the coefficient δ. The fourth step investigates the joint association between opacity, fragility and intermediation quality by analyzing Equation 4.2. This step asks whether one of the two features, opacity or fragility, subsumes the other and will strengthen or weaken any conclusions initially drawn about A1 and A2.

The creation of liquidity is essential to the existence of banks as such. It can be viewed as a necessary by-product of bank operations. Therefore an explicit behavioral hypothesis is not required to justify considering intermediation quality. Hence endogeneity due to reverse causation, as noted for regressions that involve efficiency scores as the dependent variable by for example Berger and DeYoung (1997) and Mester (1993), is likely to be a much smaller danger than if one were to investigate, for example, cost efficiency, which is known to be explicitly considered by managers. Even so the robustness checks (see Section 4.6) discuss and address these issues further, finding the results to be resilient. Still, care is needed in the interpretation of the results. That is I stress at the outset that the following analysis presents compelling evidence to suggest that certain properties of banks are associated with intermediation quality in special ways rather than to assume that these properties actually cause intermediation quality.

4.4.1. Exploratory Analyses

At the outset I provide some summary statistics as to the distributional properties of the resulting intermediation quality measures in Table 4.2. Intermediation quality defined as liquidity efficiency parametrized by SFA (GFA) using the $CATFAT$ measure of liquidity creation IQ^{CF}_{SFA} (IQ^{CF}_{GFA}). These results indicate that banks are foregoing ca. 40% (30%) of their liquidity creation potential depending on whether a parametric or nonparametric frontier is used. Efficiency scores obtained from the nonparametric generalized frontier analysis are somewhat greater. This is not surprising because GFA relaxes the assumptions of SFA regarding functional form and distribution of errors.

Statistic	IQ^{CF}_{SFA}	IQ^{CF}_{GFA}
mean	0.5868	0.7385
median	0.6045	0.7557
min	0.0001	0.0798
max	0.9841	1.0000
std	0.1595	0.0709
skewness	-0.9508	-3.4563

Table 4.2.:
Summary Statistics of Intermediation Quality.
Distributional properties computed on a yearly basis and then averaged across years. SFA indicates stochastic frontier analysis, GFA indicates generalized frontier analysis and CF indicates $CATFAT$ as specified in Berger and Bouwman (2009).

Moreover, univariate correlations can provide first intuition about the relations that obtain between opacity, fragility and intermediation quality. First, Table 4.3 shows that the intermediation quality measures are positively but only moderately correlated. This has frequently been documented for efficiency scores of different provenance (see for example Bauer, Berger, Ferrier and Humphrey, 1998). However, the highly significant and positive correlation indicates that the two measures are picking up similar information. Moreover, considering the opacity measures, these are only moderately correlated, with two out of three correlations being less than 0.05 in absolute value. Additionally, the largest correlation obtains between $OPQFKN$ and $OOAJLY$, where it reaches 0.549. Next, the correlations between the fragility proxies are mostly small, variously positive and negative and plausible. Thus, for instance, both Z-Score variables are positively correlated with one another and $LAGTA$, while being negatively correlated with $CREDRSK$, $LEVRAG$ and NPL. Since higher Z-Score represents greater distance to default and hence lower fragility and the same is true of $LAGTA$, while the opposite holds for the other three variables, these relations are plausible. Moreover, $LAGTA$ is negatively associated with $CREDRSK$, $LEVRAG$ and NPL, which is again plausible. Similarly, NPL is positively correlated with both $CREDRSK$ and $LEVRAG$, which is plausible since all of these variables indicate greater fragility. Furthermore, when considering the correlations between the fragility proxies and the intermediation quality measures, negative correlations with $LAGTA$ and the Z-Score variables obtain. This suggests that higher intermediation quality banks are also more fragile. This initial impression is confirmed for IQ^{CF}_{SFA}, where positive and significant correlations obtain for $LEVRAG$ and $CREDRSK$. However, for IQ^{CF}_{GFA} these correlations are negative and significant. On the other hand, here the correlation with NPL is significantly positive. Moreover, the picture that emerges with regard to opacity is also ambiguous. Thus correlations between $OLNJLY$, $OPQFKN$ and IQ^{CF}_{SFA} suggest that banks that are more opaque are simultaneously better intermediaries. This is confirmed by the correlation between IQ^{CF}_{GFA} and $OPQFKN$. However, correlations between IQ^{CF}_{GFA} and $OOAJLY$ and $OLNJLY$ as well as those between IQ^{CF}_{SFA} and $OOAJLY$ suggest the opposite. Thus, the univariate picture is ambiguous when it comes to investigating the relations between opacity, fragility and intermediation quality. It does show however, that the available variables are consistent and provide substantial information in the sense that correlations are generally small. This is especially the case for the opacity variables where the small and negative coefficients suggest that these capture different aspects of bank opacity.

As noted, econometric issues prevent the direct investigation of the relation between opacity and absolute liquidity creation. However, from the point of view of the regulator and the general public it is ultimately the quantity of liquidity created that matters. Therefore, to ensure the practical relevance of subsequent findings, one needs to ascertain that there is in fact a substantial positive relation between $CATFAT$ and intermediation quality.

The following regression investigates whether this is the case by regressing liquidity creation, scaled by bank assets on controls, on fixed bank and time effects as well as intermediation quality. Specifically, the regression uses the same set of controls that is employed in the subsequent analysis. The specification follows this fixed effects form:

$$\begin{aligned}\frac{LC_{i,t}}{GTA_{i,t}} = \alpha &+ \beta_1 IQ^{CF}_{m,i,t} + \beta_2 BKSIZE_{i,t} + \beta_3 CE_{i,t} + \beta_4 ROA_{i,t} + \beta_5 BKHHI_{i,t} \\ &+ \beta_6 BKMSML_{i,t} + \beta_7 BKPOP_{i,t} + \beta_8 BKPDNS_{i,t} + \beta_9 BKICHG_{i,t} \\ &+ \beta_{10} MBHC_{i,t} + \beta_{11} OBHC_{i,t} + \beta_{12} MRG_{i,t} + \beta_{13} ACQ_{i,t} \\ &+ \sum_{t=1}^{17} \theta_t d_t + \nu_i + \epsilon_{i,t}.\end{aligned} \tag{4.5}$$

Table 4.3.: Correlations of Opacity, Fragility and Intermediation Quality.

Pearson correlation coefficients between opacity, fragility and intermediation quality variables. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. $LAGTA$ represents liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. IQ^{CF}_{SFA} (IQ^{CF}_{GFA}) stands for intermediation quality parametrized using SFA (GFA) and Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation.

Parameter	IQ^{CF}_{SFA}	IQ^{CF}_{GFA}	$OOAJLY$	$OLNJLY$	$OPQFKN$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
IQ^{CF}_{SFA}	1										
IQ^{CF}_{GFA}	0.1520***	1									
$OOAJLY$	-0.0931***	-0.0476***	1								
$OLNJLY$	0.1120***	-0.1120***	-0.0309***	1							
$OPQFKN$	0.0630***	0.0559***	0.5490***	-0.0278***	1						
$LAGTA$	-0.2560***	-0.0793***	-0.0469***	-0.2020***	-0.188***	1					
$LEVRAG$	0.0956***	-0.0201***	0.0598***	0.0213***	-0.0411***	-0.2050***	1				
NPL	-0.00280	0.1620***	0.1110***	-0.0512***	0.1570***	-0.2130***	0.0158***	1			
$CREDRSK$	0.1070***	-0.1870***	0.1190***	0.0504***	0.2130***	-0.4520***	-0.0234***	0.2210***	1		
$ZIND_{MA(3)}$	-0.0093***	-0.0009	-0.0096***	-0.0003	-0.0109***	0.0107***	-0.0138***	-0.0177***	-0.0253***	1	
$ZIND_{pool}$	-0.0842***	-0.1060***	-0.1230***	0.0838***	-0.1250***	0.2990***	-0.6740***	-0.2880***	-0.2570***	0.0229***	1

Here $m \in \{SFA, GFA\}$ and $LC = CATFAT$. Unreported regressions alternatively include lags of the independent variables to allow for gradual adaptation of intermediation quality to changes in bank behavior and find qualitatively similar results. Results are reported in Table 4.4 and show that larger ($BKSIZE$), more profitable (ROA) and cost efficient (CE) banks are better creators of liquidity. Also banks that favor more populous ($BKPOP$) markets where larger banks are active ($BKMSML$), tend to produce more liquidity. Bank holding companies also produce more liquidity than non-holding companies ($MBHC, OBHC$), while recent merger- and acquisition behavior seems to be unimportant for liquidity creation (MRG, ACQ). More importantly, the IQ^{CF}_{SFA} and IQ^{CF}_{GFA} measures of intermediation quality are positively and highly significantly associated with liquidity creation. This shows that intermediation quality matters for the quantity of liquidity created.

Parameter	(1)	(2)
IQ^{CF}_{SFA}	0.333***	
	(54.96)	
IQ^{CF}_{GFA}		0.188***
		(28.99)
$BKSIZE$	0.0215***	0.0167***
	(10.21)	(7.51)
CE	0.372***	-0.0456**
	(16.91)	(-2.09)
ROA	1.080***	1.437***
	(16.24)	(19.87)
$BKHHI$	0.00367	0.00298
	(0.73)	(0.52)
$BKMSML$	0.0260***	0.0119***
	(9.00)	(3.67)
$BKPOP$	0.0140***	0.0164***
	(10.31)	(10.73)
$BKPDNS$	-0.00275	-0.000125
	(-0.90)	(-0.04)
$BKICHG$	-0.00213	-0.0118*
	(-0.39)	(-1.96)
$MBHC$	0.0174***	0.0309***
	(5.45)	(8.71)
$OBHC$	0.0166***	0.0240***
	(6.74)	(8.56)
MRG	0.0195	0.000684
	(0.54)	(0.02)
ACQ	-0.00124	-0.00189
	(-0.78)	(-1.10)
Constant	-0.732***	-0.271***
	(-21.18)	(-7.79)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.460	0.355
N	118164	118164

Table 4.4.:
Liquidity Creation and Intermediation Quality.
Coefficients from regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by gross total assets. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Monetary values are in 2005 US Dollars. IQ^{CF}_{SFA} (IQ^{CF}_{GFA}) stands for intermediation quality parametrized using SFA (GFA) and the $CATFAT$ measure of liquidity creation from Berger and Bouwman (2009). Variables are winsorized at the 0.01 and 0.99 percentiles.

4.4.2. Analysis of Intermediation Quality

The first step of the main analysis is to investigate drivers of intermediation quality. The principal results use $CATFAT$ as the measure of liquidity creation on which the intermediation quality estimates are based and are provided in Table 4.5. The Appendix (B.2.1) reports these analyses using $CATNONFAT$ as the basis for the parametrization of intermediation quality with qualitatively similar results. Specifically, similarly to Demerjian, Lev and McVay (2012), I estimate the following pooled Tobit regression because the dependent variable is censored.[5]:

$$\begin{aligned} IQ^{CF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_{i,t}. \end{aligned} \tag{4.6}$$

Here $IQ^{CF}_{m,i,t}$ stands for intermediation quality with $m \in \{SFA, GFA\}$, d_t is a set of year dummies. The remaining variables are as previously defined.

The main findings focus on Specification 1, which uses SFA, and are as follows. First, from the coefficient on $BKSIZE$, small banks' utilization of inputs to create outputs, appears to be more conducive to the creation of liquidity. Overall this finding implies that larger banks tend to be further away from the "liquidity creation frontier" than smaller banks. In other words, in the present sample, large banks are producing large amounts of liquidity. However their efficiency scores imply that they require disproportionately greater quantities of assets and liabilities to do so relative to small banks. This makes them less efficient from a frontier perspective. Initially this result may appear puzzling since it seems to imply that the frontier fits smaller banks more tightly. Intuitively one might expect that banks which produce greater quantities of the output should be systematically closer to the frontier. However this kind of reasoning would

[5] See e.g. Pitt and Lee (1981) for an example of this approach. This two stage method is chosen over the single stage estimation of Battese and Coelli (1995) for two reasons. First, the present dataset contains a number of unusual time periods (e.g. the financial crisis 2007-2009). Estimating a panel data model may thus confound the analysis more than elucidate it. In addition, a panel Tobit approach was abandoned due to non-convergence of the estimates. Second, the proxy for intermediation quality, liquidity efficiency, has so far not been investigated in the literature and there is no theory that explains the mechanics of how banks generate liquidity. Therefore including into the first stage efficiency estimation variables that influence the shape or location of the frontier may be inferior to the two stage approach due to confounding effects and lack of a benchmark model.

require that there be a linear relationship between the absolute value of intermediation and liquidity efficiency. Yet this need not be the case because the efficiency scores are related to the absolute liquidity creation data in a nonlinear fashion. This holds for both the GFA and SFA results and means that, ex ante, it is not possible to say anything about the relation between bank size and efficiency. This also implies that, ex post, it is possible to observe greater efficiency in liquidity creation for either large or small banks.

This finding suggests that there may exist diseconomies of scale in terms of liquidity creation, which is in and of itself an interesting question for future study. Interestingly this result may contribute to resolving the puzzle noted by Berger and Bouwman (2009), namely that small banks appear to be creating very little, if any, liquidity in the absolute sense. It seems that while they may not be creating a large dollar amount of liquidity, they are doing this in a very efficient manner, quite possibly by catering to small localized markets. Examples could be microstructure effects such as relationship lending and access to local deposit markets. Small banks are also less likely to be strongly supervised by regulators, which will allow them to pursue a more aggressive capital structure. They are also likely to be more manageable in the sense that they can more precisely align assets and liabilities and will thus likely hold smaller quantities of assets and liabilities that are unproductive from the perspective of Berger and Bouwman's (2009) liquidity creation measure. Large banks on the other hand may see the need to hold greater quantities of liquid assets as they are more likely to face erratic demand for deposits and lending due to their regional diversification.

Better intermediaries, are also more profitable (ROA). This resonates with the findings of Berger and Bouwman (2009), who note that absolute liquidity creation is positively value relevant. Although the present results cannot be compared directly with those of Berger and Bouwman (2009) since absolute liquidity creation and intermediation quality are two related but quite distinct variables, this qualitative similarity is reassuring. Cost efficiency (CE) is negatively related to intermediation quality. There is no reasonable prior that could be imposed on cost efficiency as an explanatory variable for intermediation quality. On the one hand, a positive association might be expected as the efficiency measures share a functional form and information set. On the other hand, cost efficiency measures optimizing behavior of banks along an entirely different dimension. Furthermore, banks that operate in less concentrated markets ($BKHHI$) with fewer large competitors ($BKMSML$) and high affluence ($BKICHG$) are more efficiently creating liquidity. This is again plausible since large competitors tend to increase the need for resource allocation on efforts such as marketing that are not in and of themselves conducive to balance sheet liquidity or efficient intermediation. Furthermore, more affluent markets will tend to have greater access to deposits, which in turn should improve banks' ability to intermediate. Holding companies tend to be more efficient liquidity creators ($MBHC$, $OBHC$) and recent acquisitions (ACQ) tend to facilitate intermediation quality as well. I obtain similar patterns as in the baseline case when considering IQ^{CF}_{GFA} in Specification 2. This holds in terms of $BKSIZE$, $BKPOP$, $BKPDNS$, $MBHC$, $OBHC$, and ACQ. The two measures of intermediation quality disagree significantly only for ROA and $BKPDNS$. Overall, the results on the drivers of intermediation quality are intuitive. Equipped with the knowledge of signs and significances on these controls, one can investigate the alternative hypotheses developed at the outset with greater confidence.

Parameter	(1)	(2)
$BKSIZE$	-0.0332***	-0.0296***
	(-26.21)	(-60.82)
CE	-1.512***	0.00197
	(-40.85)	(0.18)
ROA	1.024***	-0.279***
	(8.20)	(-7.63)
$BKHHI$	-0.0131	0.00296
	(-1.40)	(1.49)
$BKMSML$	-0.00801	0.00338**
	(-1.46)	(2.16)
$BKPOP$	0.00506***	0.00318***
	(5.58)	(13.34)
$BKPDNS$	-0.0119***	0.000994***
	(-9.11)	(3.01)
$BKICHG$	0.0695***	0.0636***
	(5.63)	(15.50)
$MBHC$	0.0680***	0.00848***
	(18.25)	(8.84)
$OBHC$	0.0418***	0.00544***
	(12.75)	(7.16)
MRG	-0.00563	0.0385
	(-0.09)	(1.06)
ACQ	0.00831***	0.00216**
	(3.22)	(2.11)
Constant	2.307***	1.031***
	(55.66)	(74.41)
Time FE	Yes	Yes
N	118164	118164

Table 4.5.:
Drivers of Intermediation Quality, Intermediation Quality Based on $CATFAT$.
Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Specification 1 is based on SFA, Specification 2 is based on GFA.

4.4.3. The Importance of Opacity for Intermediation Quality

This section disentangles A1 and A2 on the one hand from A3 on the other. The distinguishing feature is opacity. While A1 and A2 predict a positive relation between opacity and intermediation quality, A3 predicts the opposite. To investigate this, I regress my intermediation quality proxy on the same set of explanatory variables as above, adding in turn one of three alternative proxies for opacity to the regression. Two proxies come from Jones, Lee and Yeager (2012), who provide a categorization of assets into other opaque assets ($OOAJLY$), other loans ($OLNJLY$) and non-opaque categories. $OPQFKN$ represents the subset of bank assets identified as opaque by Flannery, Kwan and Nimalendran (2013). More specifically, for each $j = 1:3$ I now estimate one Tobit regression

$$\begin{aligned} IQ^{CF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,j,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_i \end{aligned} \tag{4.7}$$

where $OP_{i,j,t}$ is the jth of the three opacity proxies and $m \in \{SFA, GFA\}$.

Table 4.6 reports the results. The signs and significances on the control variables are very similar to the results in the previous section. Where opacity is concerned, I find a strong, significantly positive relation between opacity and intermediation quality using $OLNJLY$ and $OPQFKN$ in the case of IQ^{CF}_{SFA} (Specifications 1-3). This is evidence that the opacity of banks exerts a significantly positive influence on intermediation quality. The other proxy developed from Jones, Lee and Yeager (2012) ($OOAJLY$) is negative but insignificant. Interestingly, however this proxy turns significantly positive when the variables are winsorized at the 2% tails instead the 1% tails (see Appendix B.2.2 for details). Hence the insignificance of $OOAJLY$ is outlier driven and if approached appropriately this variable too supports the main findings. This is confirmed by Specifications 4-6, which use IQ^{CF}_{GFA}. Here I also find a significantly positive coefficient for $OPQFKN$. The coefficient on $OLNJLY$ is significantly negative but it represents the only significant piece of evidence that speaks against the initial interpretation. Thus, since the bulk of the evidence supports this interpretation, I accept the notion that only either A1 or A2 should remain as candidate alternatives. This leads to the rejection of both the null of no significance of opacity for intermediation quality and the alternative A3.

Table 4.6.:
Intermediation Quality and Opacity, Intermediation Quality Based on $CATFAT$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATFAT$ measure of Berger and Bouwman (2009). Specifications 1-3 use SFA and 4-6 use GFA to obtain intermediation quality.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$OOAJLY$	-0.0103			0.0243		
	(-0.23)			(1.31)		
$OLNJLY$		0.119***			-0.0658***	
		(10.02)			(-18.62)	
$OPQFKN$			0.820***			0.0966***
			(14.89)			(5.97)
$BKSIZE$	-0.0331***	-0.0324***	-0.0356***	-0.0299***	-0.0301***	-0.0299***
	(-25.21)	(-24.85)	(-27.85)	(-61.20)	(-61.21)	(-60.99)
CE	-1.511***	-1.528***	-1.526***	0.000266	0.0111	0.000264
	(-40.66)	(-41.08)	(-41.53)	(0.02)	(1.01)	(0.02)
ROA	1.015***	0.975***	1.444***	-0.257***	-0.251***	-0.229***
	(7.94)	(7.78)	(11.47)	(-6.57)	(-6.96)	(-6.13)
$BKHHI$	-0.0130	-0.0107	-0.0155*	0.00281	0.00163	0.00268
	(-1.39)	(-1.17)	(-1.68)	(1.42)	(0.80)	(1.36)
$BKMSML$	-0.00797	-0.00595	-0.0101*	0.00329**	0.00224	0.00313**
	(-1.45)	(-1.09)	(-1.86)	(2.10)	(1.45)	(2.01)
$BKPOP$	0.00506***	0.00636***	0.00532***	0.00318***	0.00246***	0.00321***
	(5.58)	(6.94)	(5.91)	(13.35)	(10.30)	(13.51)
$BKPDNS$	-0.0119***	-0.00966***	-0.0114***	0.00101***	-0.000236	0.00104***
	(-9.10)	(-7.38)	(-8.87)	(3.04)	(-0.71)	(3.19)
$BKICHG$	0.0696***	0.0672***	0.0642***	0.0634***	0.0649***	0.0630***
	(5.64)	(5.46)	(5.26)	(15.51)	(15.93)	(15.40)
$MBHC$	0.0681***	0.0631***	0.0614***	0.00822***	0.0112***	0.00771***
	(18.26)	(17.26)	(16.77)	(8.35)	(11.83)	(7.99)

Continued on next page

Table 4.6 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$OBHC$	0.0418***	0.0382***	0.0379***	0.00533***	0.00741***	0.00498***
	(12.76)	(11.90)	(11.79)	(6.96)	(9.84)	(6.56)
MRG	-0.00532	-0.00946	-0.0176	0.0378	0.0406	0.0371
	(-0.08)	(-0.14)	(-0.29)	(1.05)	(1.06)	(1.00)
ACQ	0.00834***	0.00898***	0.00473*	0.00207**	0.00179*	0.00174*
	(3.23)	(3.49)	(1.84)	(2.02)	(1.76)	(1.69)
Constant	2.306***	2.266***	2.311***	1.034***	1.054***	1.031***
	(55.37)	(53.02)	(55.87)	(74.14)	(76.47)	(74.47)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	118164	118164

4.4.4. The Influence of Fragility

This section further disentangles A1 and A2. In so doing, it investigates whether the fragility of banks is an important driver of intermediation quality. The work of Diamond and Rajan (2000, 2001) suggests that fragility disciplines banks and thus leads to the "Opacity-Fragility Hypothesis" (A2). If this alternative holds, the association between fragility and intermediation quality should be positive. On the other hand Dewatripont and Maskin (1995) and associated work suggests that fragility is in fact detrimental to the quality of financial intermediation because it reduces the hardness of budget constraints that banks impose on borrowers and thus invites poor debtors ("Opacity-Hardness Hypothesis", A1). The analyses below investigate these two alternatives. They measure fragility along several dimensions. There are four simple measures, leverage ($LEVRAG$), nonperforming loans as a fraction of total loans (NPL), the ratio of risk weighted assets to total assets ($CREDRSK$) and the ratio of liquid assets over total assets ($LAGTA$). Moreover, two specifications of Z-Score, $ZIND_{pool}$, $ZIND_{MA(3)}$, are used to capture a bank's distance to default (De Nicoló, 2000). If A2 holds and more fragile banks are better at creating liquidity, then one would expect positive signs on leverage, nonperforming loans and risk weighted assets over total assets. Also one would expect to observe negative signs for Z-Score and $LAGTA$. The opposite is the expectation if A1 holds. Section 4.4.4.1 investigates the effects of fragility on liquidity creation in isolation. This will allow for a better assessment whether opacity and fragility subsume similar intermediation quality effects and it will broadly distinguish between A1 and A2. In order to ensure valid results, the subsequent analysis then proceeds to investigate the results with opacity and fragility jointly included in Section 4.4.4.2.

4.4.4.1. Fragility and Intermediation Quality

This section takes a first step towards disentangling A1 and A2 by examining fragility. It first provides results on the relation between intermediation quality and fragility alone. The regressions are again Tobit and take the following form:

$$
\begin{aligned}
IQ^{CF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\
&+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\
&+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \delta FRAG_{i,k,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_i,
\end{aligned}
\tag{4.8}
$$

where $FRAG_{i,t,k}$ is the kth of the six fragility proxies and $m \in \{SFA, GFA\}$. Table 4.7 reports the corresponding results.

The signs of the control variables are similar relative to the previous analyses. As regards fragility there is clear evidence that more fragile banks are better intermediaries. Specifically, higher intermediation quality banks have fewer liquid assets ($LAGTA$), are more highly leveraged ($LEVRAG$) and hold lower quality loan portfolios (NPL). These banks also hold greater quantities of risk weighted assets ($CREDRSK$) and are closer to default ($ZIND_{MA(3)}, ZIND_{pool}$). All these signs are as would be expected under A2. All of the above findings, with the exception of NPL, where the coefficient is significantly negative in the GFA case, hold for both IQ^{CF}_{SFA} and IQ^{CF}_{GFA} (Specifications 1-6 and 7-12 respectively). Thus, overall, the overwhelming majority of the evidence points to a rejection of A1 in favor of A2.

Table 4.7.: Intermediation Quality and Fragility, Intermediation Quality Based on $CATFAT$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATFAT$ measure of Berger and Bouwman (2009) and on SFA in Specifications 1-6 and uses GFA in Specifications 7-12.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$LAGTA$	-0.328***						-0.0774***					
	(-31.40)						(-34.64)					
$LEVRAG$		0.00557***						0.00379***				
		(11.32)						(32.51)				
NPL			0.133*						-0.00822			
			(1.94)						(-0.44)			
$CREDRSK$				0.452***						0.0992***		
				(39.08)						(35.30)		
$ZIND_{MA(3)}$					-0.00189***						-0.000757***	
					(-7.27)						(-8.00)	
$ZIND_{pool}$						-0.00392***						-0.00202***
						(-11.85)						(-30.71)
$BKSIZE$	-0.0371***	-0.0350***	-0.0332***	-0.0388***	-0.0326***	-0.0349***	-0.0306***	-0.0309***	-0.0296***	-0.0309***	-0.0294***	-0.0305***
	(-29.83)	(-27.11)	(-26.19)	(-30.73)	(-25.33)	(-27.07)	(-64.00)	(-63.38)	(-60.81)	(-65.71)	(-59.95)	(-62.82)
CE	-1.487***	-1.474***	-1.511***	-1.488***	-1.507***	-1.462***	0.00775	0.0274**	0.00191	0.00718	0.00766	0.0275**
	(-42.78)	(-39.62)	(-40.80)	(-42.79)	(-40.43)	(-39.20)	(0.72)	(2.48)	(0.17)	(0.67)	(0.68)	(2.48)
ROA	1.258***	1.457***	1.104***	1.208***	1.174***	1.860***	-0.223***	0.0164	-0.284***	-0.238***	-0.295***	0.152***
	(10.90)	(11.94)	(8.23)	(10.57)	(9.06)	(14.75)	(-6.40)	(0.46)	(-7.19)	(-6.78)	(-7.78)	(4.15)
$BKHHI$	-0.00583	-0.0117	-0.0138	-0.00862	-0.0152	-0.0115	0.00468**	0.00392**	0.00300	0.00395**	0.00299	0.00379**
	(-0.69)	(-1.26)	(-1.47)	(-1.04)	(-1.59)	(-1.24)	(2.55)	(2.07)	(1.51)	(2.13)	(1.49)	(1.99)
$BKMSML$	-0.0228***	-0.00800	-0.00772	-0.0142***	-0.00867	-0.00848	-0.000113	0.00339**	0.00336**	0.00202	0.00356**	0.00314**
	(-4.53)	(-1.47)	(-1.40)	(-2.90)	(-1.55)	(-1.57)	(-0.08)	(2.25)	(2.15)	(1.36)	(2.24)	(2.08)
$BKPOP$	0.00463***	0.00450***	0.00502***	0.00398***	0.00492***	0.00451***	0.00308***	0.00280***	0.00318***	0.00294***	0.00315***	0.00290***
	(5.57)	(5.04)	(5.54)	(4.93)	(5.35)	(5.07)	(13.80)	(12.34)	(13.36)	(13.04)	(12.97)	(12.71)
$BKPDNS$	-0.0132***	-0.0116***	-0.0119***	-0.00968***	-0.0115***	-0.0117***	0.000676**	0.00121***	0.000995***	0.00148***	0.00106***	0.00110***
	(-10.91)	(-8.94)	(-9.12)	(-8.23)	(-8.74)	(-9.06)	(2.20)	(3.86)	(3.02)	(4.77)	(3.20)	(3.50)
$BKICHG$	0.0861***	0.0557***	0.0718***	0.0798***	0.0697***	0.0523***	0.0675***	0.0542***	0.0635***	0.0659***	0.0638***	0.0547***
	(7.44)	(4.55)	(5.83)	(6.91)	(5.65)	(4.28)	(16.88)	(13.45)	(15.45)	(16.45)	(15.48)	(13.51)
$MBHC$	0.0541***	0.0600***	0.0680***	0.0533***	0.0681***	0.0583***	0.00521***	0.00306***	0.00848***	0.00525***	0.00857***	0.00350***
	(16.04)	(16.59)	(18.26)	(16.20)	(17.91)	(16.23)	(5.76)	(3.32)	(8.84)	(5.76)	(8.80)	(3.79)
$OBHC$	0.0333***	0.0354***	0.0417***	0.0316***	0.0427***	0.0337***	0.00344***	0.00109	0.00544***	0.00320***	0.00547***	0.00129*
	(11.42)	(11.05)	(12.74)	(11.14)	(12.71)	(10.62)	(4.87)	(1.51)	(7.16)	(4.45)	(7.09)	(1.78)
MRG	-0.0178	0.00229	-0.00550	-0.0368	-0.00781	0.00215	0.0356	0.0439	0.0385	0.0316	0.0375	0.0425
	(-0.28)	(0.03)	(-0.09)	(-0.51)	(-0.12)	(0.03)	(0.99)	(1.25)	(1.06)	(0.94)	(1.04)	(1.24)
ACQ	0.00429*	0.00987***	0.00837***	0.00470*	0.00820***	0.0101***	0.00121	0.00322***	0.00215**	0.00136	0.00200*	0.00306***

Continued on next page

Table 4.7 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(1.73)	(3.85)	(3.25)	(1.94)	(3.17)	(3.92)	(1.22)	(3.24)	(2.11)	(1.37)	(1.96)	(3.07)
Constant	2.468***	2.248***	2.304***	2.101***	2.297***	2.348***	1.069***	0.990***	1.031***	0.985***	1.024***	1.051***
	(62.91)	(53.47)	(55.49)	(51.72)	(55.05)	(57.00)	(79.01)	(71.99)	(74.48)	(74.79)	(73.89)	(77.17)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	-0.375	-0.264	-0.254	-0.400	-0.255	-0.268	-1.457	-1.450	-1.429	-1.458	-1.432	-1.445
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

4.4.4.2. Intermediation Quality in the Opacity-Fragility Nexus

Results in the previous section indicate that A2, the hypothesis that more fragile banks are better intermediators of liquidity, should be accepted. The present reading of the theory advanced by Diamond and Rajan (2000, 2001) suggests that opacity and fragility are functionally similar. It might, for example, be the case that due to extensive bank regulation along the lines of Basel II, or due to a perceived too-big-to-fail policy, depositors view banks as essentially riskless as long as their signal about bank fragility is not noisy. If the signal becomes more noisy, for example due to opacity, the confidence of depositors is shaken and only then do they seriously consider running on banks. To gain more robust insight into the joint influence of opacity and fragility on intermediation quality, this section reruns the analysis including both fragility and opacity in the specification, which takes the following form.

$$\begin{aligned} IQ^{CF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,j,t} + \delta FRAG_{i,k,t} \\ &+ \sum_{t=1}^{17} \theta_t d_t + \epsilon_i. \end{aligned} \tag{4.9}$$

Results are reported in Tables 4.8-4.10. Results show across all of the analyses that neither opacity nor fragility lose their explanatory power nor do they change sign as regards intermediation quality in the vast majority of cases. $OOAJLY$ is again insignificant across most regressions although it turns positive for SFA in most instances. In addition, it turns significantly positive for the GFA-based intermediation quality measure when fragility is measured using pooled Z-Score, liquid assets over total assets and leverage. Moreover, when winsorizing at the 2% tails, $OOAJLY$ becomes significantly positive throughout (see Appendix B.2.2). When intermediation quality is measured by way of SFA, $OLNJLY$ is significantly positively associated with intermediation quality as before except when fragility is proxied by $LAGTA$ and $CREDRSK$. It remains significantly negative for the GFA-based intermediation quality. Also, NPL loses its significance when it is used to control for fragility. This points to a small degree of interaction between fragility and opacity as parametrized by $OLNJLY$. The measure derived from Flannery, Kwan and Nimalendran (2013), $OPQFKN$, maintains its positive and highly significant relation with intermediation quality throughout the analysis. Both the SFA and the GFA-based measures of intermediation quality support these findings. Taken together, this evidence suggests that intermediation quality increases with opacity regardless of whether fragility is controlled for or not. This confirms that A1 should be rejected in favor of A2.

Table 4.8.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATFAT$, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OOAJLY$	0.0224	0.0132	-0.0128	-0.0940**	0.00232	0.0203	0.0320*	0.0403**	0.0245	0.00595	0.0287	0.0401**
	(0.55)	(0.30)	(-0.29)	(-2.34)	(0.05)	(0.45)	(1.79)	(2.15)	(1.31)	(0.34)	(1.54)	(2.15)
$LAGTA$	-0.328***						-0.0776***					
	(-31.39)						(-35.03)					
$LEVRAG$		0.00558***						0.00382***				
		(11.24)						(32.50)				
NPL			0.135*						-0.0114			
			(1.96)						(-0.61)			
$CREDRSK$				0.453***						0.0992***		
				(39.27)						(34.78)		
$ZIND_{MA(3)}$					-0.00188***						-0.000737***	
					(-7.32)						(-7.81)	
$ZIND_{pool}$						-0.00393***						-0.00204***
						(-11.78)						(-30.84)
$BKSIZE$	-0.0373***	-0.0351***	-0.0330***	-0.0378***	-0.0326***	-0.0351***	-0.0309***	-0.0313***	-0.0299***	-0.0309***	-0.0297***	-0.0310***
	(-28.47)	(-26.05)	(-25.17)	(-29.12)	(-24.49)	(-26.08)	(-65.36)	(-64.22)	(-61.16)	(-66.00)	(-60.20)	(-63.71)
CE	-1.489***	-1.475***	-1.510***	-1.481***	-1.507***	-1.463***	0.00553	0.0248**	0.000168	0.00676	0.00567	0.0250**
	(-42.56)	(-39.50)	(-40.60)	(-42.54)	(-40.29)	(-39.11)	(0.51)	(2.21)	(0.01)	(0.62)	(0.50)	(2.22)
ROA	1.277***	1.469***	1.094***	1.126***	1.176***	1.880***	-0.195***	0.0540	-0.264***	-0.233***	-0.270***	0.191***
	(10.80)	(11.59)	(8.05)	(9.58)	(8.86)	(14.25)	(-5.19)	(1.39)	(-6.40)	(-6.16)	(-6.63)	(4.75)
$BKHHI$	-0.00596	-0.0118	-0.0137	-0.00802	-0.0152	-0.0116	0.00449**	0.00367*	0.00287	0.00391**	0.00281	0.00355*
	(-0.70)	(-1.27)	(-1.46)	(-0.97)	(-1.60)	(-1.26)	(2.45)	(1.95)	(1.45)	(2.11)	(1.41)	(1.87)
$BKMSML$	-0.0229***	-0.00805	-0.00766	-0.0138***	-0.00868	-0.00856	-0.000245	0.00323**	0.00326**	0.00200	0.00345**	0.00298**
	(-4.55)	(-1.48)	(-1.40)	(-2.83)	(-1.56)	(-1.59)	(-0.17)	(2.15)	(2.09)	(1.35)	(2.17)	(1.98)
$BKPOP$	0.00463***	0.00450***	0.00501***	0.00396***	0.00492***	0.00451***	0.00308***	0.00280***	0.00319***	0.00294***	0.00315***	0.00290***
	(5.57)	(5.04)	(5.54)	(4.91)	(5.35)	(5.07)	(13.81)	(12.35)	(13.37)	(13.03)	(12.97)	(12.72)
$BKPDNS$	-0.0132***	-0.0115***	-0.0119***	-0.00972***	-0.0115***	-0.0117***	0.000692**	0.00124***	0.00101***	0.00148***	0.00107***	0.00113***
	(-10.89)	(-8.92)	(-9.12)	(-8.26)	(-8.73)	(-9.04)	(2.24)	(3.92)	(3.05)	(4.77)	(3.23)	(3.56)
$BKICHG$	0.0859***	0.0555***	0.0719***	0.0807***	0.0697***	0.0520***	0.0672***	0.0537***	0.0632***	0.0658***	0.0636***	0.0543***
	(7.43)	(4.54)	(5.85)	(7.00)	(5.65)	(4.27)	(16.88)	(13.41)	(15.44)	(16.48)	(15.49)	(13.47)
$MBHC$	0.0539***	0.0599***	0.0681***	0.0542***	0.0681***	0.0580***	0.00486***	0.00259***	0.00822***	0.00519***	0.00828***	0.00303***

Continued on next page

Table 4.8 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(15.95)	(16.47)	(18.27)	(16.51)	(17.89)	(16.08)	(5.27)	(2.70)	(8.34)	(5.58)	(8.30)	(3.15)
$OBHC$	0.0332***	0.0353***	0.0418***	0.0320***	0.0427***	0.0336***	0.00330***	0.000886	0.00534***	0.00318***	0.00536***	0.00108
	(11.38)	(11.01)	(12.75)	(11.26)	(12.71)	(10.57)	(4.62)	(1.20)	(6.96)	(4.39)	(6.88)	(1.47)
MRG	-0.0184	0.00191	-0.00512	-0.0341	-0.00788	0.00157	0.0347	0.0427	0.0378	0.0315	0.0366	0.0413
	(-0.29)	(0.03)	(-0.08)	(-0.48)	(-0.12)	(0.02)	(0.98)	(1.24)	(1.05)	(0.93)	(1.02)	(1.23)
ACQ	0.00421*	0.00983***	0.00841***	0.00501**	0.00819***	0.0100***	0.00109	0.00309***	0.00207**	0.00134	0.00191*	0.00293***
	(1.70)	(3.82)	(3.26)	(2.07)	(3.17)	(3.90)	(1.10)	(3.10)	(2.02)	(1.35)	(1.86)	(2.93)
Constant	2.471***	2.249***	2.302***	2.087***	2.297***	2.351***	1.073***	0.995***	1.034***	0.986***	1.028***	1.057***
	(62.19)	(53.36)	(55.16)	(51.27)	(54.83)	(56.66)	(79.02)	(72.04)	(74.16)	(74.11)	(73.48)	(77.03)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

Table 4.9.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATFAT$, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OLNJLY$	-0.0293***	0.110***	0.118***	-0.0831***	0.115***	0.106***	-0.113***	-0.0724***	-0.0660***	-0.128***	-0.0663***	-0.0734***
	(-2.64)	(9.48)	(10.03)	(-7.65)	(9.55)	(9.19)	(-30.44)	(-20.69)	(-18.73)	(-35.64)	(-18.49)	(-20.92)
$LAGTA$	-0.336***						-0.107***					
	(-31.47)						(-45.16)					
$LEVRAG$		0.00522***						0.00402***				
		(10.85)						(34.36)				
NPL			0.0629						0.0308*			
			(0.93)						(1.71)			
$CREDRSK$				0.485***						0.150***		
				(41.36)						(51.53)		
$ZIND_{MA(3)}$					-0.00164***						-0.000898***	
					(-6.51)						(-9.41)	

Continued on next page

Table 4.9 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ZIND_{pool}$						-0.00366***						-0.00220***
						(-11.34)						(-32.85)
$BKSIZE$	-0.0374***	-0.0341***	-0.0324***	-0.0398***	-0.0318***	-0.0340***	-0.0317***	-0.0314***	-0.0301***	-0.0324***	-0.0298***	-0.0311***
	(-29.95)	(-25.80)	(-24.85)	(-31.76)	(-24.06)	(-25.78)	(-64.79)	(-63.69)	(-61.21)	(-69.03)	(-60.40)	(-63.16)
CE	-1.483***	-1.492***	-1.528***	-1.475***	-1.524***	-1.480***	0.0258**	0.0390***	0.0114	0.0277***	0.0175	0.0400***
	(-42.59)	(-39.94)	(-41.06)	(-42.78)	(-40.75)	(-39.55)	(2.54)	(3.60)	(1.04)	(2.79)	(1.59)	(3.69)
ROA	1.275***	1.384***	1.013***	1.256***	1.113***	1.761***	-0.155***	0.0642*	-0.232***	-0.164***	-0.260***	0.220***
	(11.06)	(11.31)	(7.52)	(11.04)	(8.56)	(13.97)	(-4.64)	(1.85)	(-5.97)	(-4.93)	(-6.94)	(6.15)
$BKHHI$	-0.00625	-0.00956	-0.0110	-0.00998	-0.0127	-0.00946	0.00305*	0.00250	0.00146	0.00185	0.00157	0.00237
	(-0.73)	(-1.05)	(-1.20)	(-1.20)	(-1.36)	(-1.04)	(1.69)	(1.31)	(0.72)	(1.04)	(0.77)	(1.24)
$BKMSML$	-0.0237***	-0.00609	-0.00582	-0.0161***	-0.00668	-0.00661	-0.00343**	0.00213	0.00230	-0.000905	0.00241	0.00184
	(-4.70)	(-1.12)	(-1.06)	(-3.31)	(-1.20)	(-1.23)	(-2.46)	(1.45)	(1.50)	(-0.66)	(1.54)	(1.25)
$BKPOP$	0.00429***	0.00575***	0.00634***	0.00298***	0.00622***	0.00571***	0.00179***	0.00198***	0.00244***	0.00141***	0.00240***	0.00207***
	(5.05)	(6.35)	(6.91)	(3.61)	(6.67)	(6.34)	(8.34)	(8.78)	(10.25)	(6.62)	(9.88)	(9.12)
$BKPDNS$	-0.0138***	-0.00951***	-0.00968***	-0.0111***	-0.00940***	-0.00969***	-0.00156***	-0.000125	-0.000247	-0.000676**	-0.000173	-0.000258
	(-11.21)	(-7.33)	(-7.39)	(-9.35)	(-7.09)	(-7.50)	(-5.22)	(-0.40)	(-0.74)	(-2.33)	(-0.52)	(-0.82)
$BKICHG$	0.0871***	0.0544***	0.0683***	0.0822***	0.0675***	0.0513***	0.0712***	0.0550***	0.0654***	0.0695***	0.0651***	0.0554***
	(7.52)	(4.46)	(5.57)	(7.12)	(5.49)	(4.22)	(18.28)	(13.77)	(16.03)	(17.88)	(15.90)	(13.79)
$MBHC$	0.0550***	0.0560***	0.0631***	0.0556***	0.0635***	0.0546***	0.00858***	0.00571***	0.0112***	0.00886***	0.0113***	0.00607***
	(16.26)	(15.64)	(17.27)	(16.91)	(16.98)	(15.31)	(10.03)	(6.35)	(11.85)	(10.51)	(11.75)	(6.76)
$OBHC$	0.0340***	0.0325***	0.0382***	0.0333***	0.0393***	0.0311***	0.00605***	0.00300***	0.00740***	0.00590***	0.00746***	0.00312***
	(11.61)	(10.27)	(11.89)	(11.74)	(11.91)	(9.89)	(9.01)	(4.24)	(9.83)	(8.87)	(9.74)	(4.42)
MRG	-0.0171	-0.00175	-0.00939	-0.0364	-0.0113	-0.00179	0.0382	0.0466	0.0407	0.0323	0.0395	0.0452
	(-0.27)	(-0.03)	(-0.14)	(-0.52)	(-0.17)	(-0.03)	(0.97)	(1.26)	(1.06)	(0.89)	(1.03)	(1.24)
ACQ	0.00403	0.0104***	0.00900***	0.00396	0.00888***	0.0105***	0.000204	0.00288***	0.00180*	0.000234	0.00161	0.00273***
	(1.62)	(4.05)	(3.49)	(1.64)	(3.44)	(4.11)	(0.21)	(2.93)	(1.78)	(0.24)	(1.59)	(2.77)
Constant	2.482***	2.213***	2.264***	2.115***	2.257***	2.308***	1.123***	1.013***	1.053***	1.007***	1.047***	1.079***
	(63.14)	(51.20)	(52.93)	(52.69)	(52.45)	(54.47)	(83.87)	(74.23)	(76.47)	(80.37)	(76.00)	(79.47)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

Table 4.10.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATFAT$, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OPQFKN$	0.562***	0.902***	0.819***	0.508***	0.852***	0.888***	0.0345**	0.148***	0.0968***	0.0268*	0.0933***	0.130***
	(11.24)	(16.14)	(14.88)	(10.10)	(15.10)	(16.04)	(2.22)	(9.55)	(5.98)	(1.73)	(5.65)	(8.41)
$LAGTA$	-0.319***						-0.0769***					
	(-30.88)						(-33.96)					
$LEVRAG$		0.00628***						0.00391***				
		(12.71)						(33.80)				
NPL			0.106						-0.0115			
			(1.56)						(-0.62)			
$CREDRSK$				0.441***						0.0987***		
				(38.58)						(34.75)		
$ZIND_{MA(3)}$					-0.00159***						-0.000725***	
					(-6.33)						(-7.73)	
$ZIND_{pool}$						-0.00424***						-0.00206***
						(-12.90)						(-31.67)
$BKSIZE$	-0.0386***	-0.0379***	-0.0356***	-0.0402***	-0.0352***	-0.0376***	-0.0306***	-0.0313***	-0.0299***	-0.0309***	-0.0297***	-0.0309***
	(-30.77)	(-28.86)	(-27.84)	(-31.53)	(-27.05)	(-28.78)	(-63.97)	(-63.95)	(-60.99)	(-65.49)	(-60.09)	(-63.28)
CE	-1.498***	-1.486***	-1.525***	-1.498***	-1.521***	-1.474***	0.00711	0.0256**	0.000177	0.00668	0.00607	0.0258**
	(-43.19)	(-40.25)	(-41.48)	(-43.11)	(-41.12)	(-39.87)	(0.66)	(2.32)	(0.02)	(0.62)	(0.54)	(2.33)
ROA	1.539***	1.974***	1.507***	1.463***	1.609***	2.383***	-0.206***	0.101***	-0.236***	-0.225***	-0.247***	0.228***
	(13.17)	(15.80)	(11.13)	(12.63)	(12.31)	(18.29)	(-5.75)	(2.78)	(-5.86)	(-6.23)	(-6.36)	(6.08)
$BKHHI$	-0.00767	-0.0142	-0.0161*	-0.0102	-0.0178*	-0.0140	0.00457**	0.00351*	0.00274	0.00386**	0.00270	0.00342*
	(-0.91)	(-1.56)	(-1.73)	(-1.24)	(-1.90)	(-1.54)	(2.49)	(1.86)	(1.38)	(2.08)	(1.36)	(1.81)
$BKMSML$	-0.0239***	-0.0103*	-0.00988*	-0.0153***	-0.0108*	-0.0108**	-0.000178	0.00301**	0.00311**	0.00196	0.00333**	0.00280*
	(-4.76)	(-1.92)	(-1.82)	(-3.15)	(-1.96)	(-2.02)	(-0.12)	(2.01)	(2.00)	(1.32)	(2.10)	(1.87)
$BKPOP$	0.00482***	0.00472***	0.00529***	0.00416***	0.00517***	0.00475***	0.00309***	0.00284***	0.00321***	0.00295***	0.00318***	0.00293***
	(5.81)	(5.33)	(5.88)	(5.17)	(5.67)	(5.38)	(13.87)	(12.55)	(13.54)	(13.10)	(13.12)	(12.91)
$BKPDNS$	-0.0129***	-0.0110***	-0.0115***	-0.00947***	-0.0111***	-0.0112***	0.000697**	0.00130***	0.00105***	0.00149***	0.00111***	0.00118***
	(-10.68)	(-8.64)	(-8.88)	(-8.07)	(-8.51)	(-8.78)	(2.27)	(4.16)	(3.19)	(4.81)	(3.35)	(3.75)
$BKICHG$	0.0821***	0.0481***	0.0660***	0.0763***	0.0651***	0.0451***	0.0673***	0.0529***	0.0628***	0.0657***	0.0633***	0.0537***
	(7.14)	(3.98)	(5.43)	(6.65)	(5.34)	(3.74)	(16.86)	(13.21)	(15.34)	(16.42)	(15.41)	(13.32)
$MBHC$	0.0500***	0.0518***	0.0615***	0.0496***	0.0617***	0.0504***	0.00495***	0.00172*	0.00771***	0.00506***	0.00786***	0.00235**

Continued on next page

Table 4.10 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(14.90)	(14.57)	(16.78)	(15.18)	(16.48)	(14.24)	(5.44)	(1.86)	(7.99)	(5.50)	(8.03)	(2.53)
$OBHC$	0.0309***	0.0303***	0.0379***	0.0294***	0.0389***	0.0289***	0.00329***	0.000261	0.00498***	0.00309***	0.00505***	0.000583
	(10.66)	(9.65)	(11.78)	(10.46)	(11.79)	(9.25)	(4.64)	(0.36)	(6.57)	(4.28)	(6.55)	(0.80)
MRG	-0.0257	-0.00986	-0.0175	-0.0435	-0.0200	-0.0102	0.0351	0.0419	0.0371	0.0313	0.0361	0.0407
	(-0.42)	(-0.16)	(-0.29)	(-0.62)	(-0.33)	(-0.16)	(0.97)	(1.17)	(1.00)	(0.92)	(0.98)	(1.16)
ACQ	0.00194	0.00614**	0.00478*	0.00257	0.00450*	0.00634**	0.00106	0.00261***	0.00173*	0.00125	0.00160	0.00252**
	(0.79)	(2.41)	(1.86)	(1.07)	(1.75)	(2.50)	(1.07)	(2.62)	(1.68)	(1.26)	(1.56)	(2.51)
Constant	2.466***	2.244***	2.309***	2.109***	2.301***	2.355***	1.068***	0.989***	1.031***	0.986***	1.024***	1.052***
	(62.84)	(53.57)	(55.73)	(51.92)	(55.25)	(57.35)	(79.02)	(72.17)	(74.55)	(74.70)	(73.93)	(77.32)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

4.5. Additional Analysis

In order to gain further insight into the relation between the quality of financial intermediation, opacity and fragility, this section conducts a number of supplementary analyses. Specifically, it investigates further whether the effects of opacity and fragility depend on the level of opacity present. It also uses an alternative parametrization of intermediation quality to test the robustness of the results. All tables are reported in Appendix C.

4.5.1. Split Sample Analysis by Opacity

So far results have supported the argument that opacity and fragility function in similar ways when it comes to disciplining banks and thus facilitate intermediation quality. However, an interesting additional question is whether the effects of opacity and fragility depend on the level of opacity present. Thus, while the theory is silent in this respect, it seems plausible to suppose that if opacity becomes excessive, it will impair a bank's ability to do business. The danger of a run will become so imminent that bank management is preoccupied with preventing this event more than with conducting intermediation. This is because opacity exacerbates the effect of any fragility, which the bank may already be experiencing.

To investigate this conjecture, I split the sample by opacity. Specifically, I rerun the analyses separately for the first and fourth quartiles of the opacity distribution as measured by the $OOAJLY$, $OLNJLY$ and $OPQFKN$ variables. These results are tabulated in Appendix B.1.1. Findings show that for low opacity banks (Q1), the results are as in the main analysis. Specifically, the fragility proxies $LAGTA$, $ZIND_{MA(3)}$ and $ZIND_{pool}$ are significantly negatively associated with intermediation quality, while $LEVRAG$, NPL and $CREDRSK$ exhibit a significantly positive relation. This indicates that low opacity banks' intermediation quality benefits from fragility. Furthermore, all three opacity variables $OOAJLY$, $OLNJLY$ and $OPQFKN$ are significantly positively associated with intermediation quality in a large majority of instances; both these findings are consistent with A2. However, in high opacity banks only $OPQFKN$ remains significantly positive. When splitting the sample by $OOAJLY$, both $OOAJLY$ and $OLNJLY$ become significantly negative. When splitting by $OLNJLY$, both $OOAJLY$ and $OLNJLY$ become insignificantly negative. When splitting by $OPQFKN$, $OOAJLY$ and $OLNJLY$ are often significantly negative for high opacity banks. Moreover, this is the only instance when a coefficient on $OPQFKN$ turns negative. Furthermore, when considering the fragility controls, three of these become insignificant ($LEVRAG$, $ZIND_{MA(3)}$, $ZIND_{pool}$) and one switches sign (NPL). This indicates that in high opacity banks, reducing fragility or opacity is beneficial for intermediation quality or that fragility is of no importance.

Taken together, this suggests that the effects of opacity and fragility are dependent on the level of opacity that is already present. An excessive level of opacity reduces the disciplining mechanism exerted by fragility in the Diamond and Rajan (2000, 2001) models because sceptical depositors may find it difficult to accurately evaluate the fragility of the bank if it is extremely opaque. An additional, analysis can further make the explanation that depositors find it difficult to evaluate bank fragility if opacity is excessive more robust. Thus I split the sample by some of the fragility proxies (Z-Score, leverage and nonperforming loans) and rerun the analysis (unreported). If the explanation given above for the differential impact of opacity is false, one should expect a similar pattern in this additional analysis. Concretely, one would expect that for high fragility banks fragility and opacity become insignificant or detrimental in the context of intermediation quality. If, on the other hand, the explanation that high opacity clouds depositors' ability to assess banks' balance sheets and thus destroys the disciplining effects of fragility and opacity, is true one should expect a picture that is qualitatively unchanged compared with the main analysis. This is the picture that obtains when splitting the sample by some of the fragility proxies. Specifically, opacity maintains sign and significance and in fact for high fragility firms, the previously insignificantly negative $OOAJLY$ tends to become significantly positive. Fragility, on the other hand, exhibits a virtually identical pattern as in the main analysis and hence the results remain unreported. Together this analysis shows that opacity and fragility are functionally similar but nonetheless distinct features of banks, which have direct bearing on intermediation quality.

4.5.2. An Alternative Measure of Bank Intermediation

Section 4.3 has briefly discussed the Deep and Schaefer (2004) liquidity gap measure. This measure is more restrictive in its understanding of liquidity creation, which it defines as the gap between liquid assets and liquid liabilities. Its underlying assumption is that whatever liquid liabilities are not used in financing liquid assets are employed in financing assets of longer duration respectively lower liquidity. This metric has been criticized by, for example, Berger and Bouwman (2009) because it does not include important categories of assets such as off-balance-sheet items and does not consider liquidity destruction, which invariably occurs in the course of banking business if, for instance, long term liabilities are used to finance short term assets. Furthermore, the liquidity transformation gap does not directly capture the "quality" of financial intermediation but rather tries to approximate its quantity. However, from the econometric viewpoint, this measure has some advantages over the Berger and Bouwman (2009) measures in that it is less likely to be collinear or trivially correlated with the opacity and fragility proxies. Therefore I use this alternative measure of bank intermediation to verify the results. Specifically I run a fixed effects regression with time and bank effects and bank level clustering of the following form:

$$\begin{aligned} LTG_{i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,t,j} + \delta FRAG_{i,t,k} \\ &+ \sum_{t=1}^{17} \theta_t d_t + \nu_i + \epsilon_{i,t}. \end{aligned} \tag{4.10}$$

Here LTG is the liquidity transformation gap scaled by total assets, all regressors are as previously defined and ν is a bank fixed effect. This regression is run three times, once unmodified, once setting γ to zero and once setting δ to zero for each opacity (fragility) measure j (k). This replicates the steps of the main analysis. A succinct discussion of these tables is given below, while a more complete discussion and the tables themselves are reported in Section B.1.2 of the appendix for brevity.

Given that this is a conceptually entirely different measure of the intermediation activity of banks, and that a different econometric parametrization is used for inference, the results exhibit a remarkable similarity with the main analysis. Thus, in all regressions the coefficients on $OLNJLY$ and $OPQFKN$ are significantly positive (the coefficient on $OOAJLY$ is significantly negative), affirming the importance of opacity in the context of financial intermediation and inducing the rejection of A3 in favor of A1 or A2. Furthermore, the proxies for bank fragility display an identical pattern as before. Thus, higher intermediation quality banks have fewer liquid assets, higher leverage and more risk weighted assets ($LAGTA$, $LEVRAG$ and $CREDRSK$). They also have a higher level of nonperforming loans (NPL) and lower distance to default ($ZIND_{pool}$). These findings continue to hold when both opacity and fragility are included in the regression. This is strong evidence for the robustness of the claim that A1 should be rejected in favor of A2.

4.6. Robustness Checks

This section conducts a number of checks for the robustness of the reported results.

The first step is to check that the results are not driven by data preprocessing, which in the present case is comprised of winsorization at the 1% and 99% level. Rerunning the main analyses without winsorizing gives weaker but qualitatively similar results (unreported). Moreover, rerunning the main analyses with winsorization at the 2% tails yields results that support the main findings in a very emphatic way. Specifically, the previously insignificant $OOAJLY$ is now positively significantly associated with intermediation quality throughout the analysis (see Appendix B.2.2 for results and a detailed discussion).

Berger and DeYoung (1997) note potential endogeneity of regressors when efficiency is a dependent variable due to reverse causation. I have given plausible reasons why this problem should be much less prevalent in the present case. Specifically, cost, revenue, and profit efficiency are likely to be known and targeted by management. Liquidity efficiency, however, is not only a novel concept it is also not clear how it would enter the managerial decision making process. Furthermore, the set of covariates used in this study is based around variables that are difficult for management to influence at least in the short run (organizational form, geographical location). Therefore it is much less likely that endogeneity obtains in the present case. However, to alleviate this concern Berger and DeYoung (1997) rest their analysis on both multi and univariate regressions. They argue that potentially endogenous variables will be likely to change sign in the uni and multivariate case. Thus, I also rerun all regressions using only one independent variable and a constant to determine that signs and significances of the correlates used are the same as in the multivariate case. This check holds for all variables except bank level population ($BKPOP$). Since re-estimating all regressions omitting this explanatory variable yields results that are virtually unchanged these findings remain untabulated.

One important robustness check is to investigate the results that obtain when $CAT-NONFAT$ is used as the proxy for liquidity creation in parametrizing the intermediation quality measure. This analysis, along with a more extensive discussion, is reported in Appendix B.2.1. Results are again extremely similar to the main findings. In fact, while the opacity proxy $OLNJLY$ was significantly negative when intermediation quality was parametrized using GFA, this effect has now vanished and a significantly positive coefficient obtains. This shows the robustness of the influence of opacity on intermediation quality. In addition, the fragility results are also robust. This holds also when both opacity and fragility are included.

A further confounding factor in the analysis might be the presence of the financial crisis in which both fragility and opacity played important roles (see e.g. Brunnermeier, 2009). While this is already somewhat mitigated by preferring to estimate the intermediation quality proxy yearly rather than using a panel data efficiency model, it may still confound inference in a pooled Tobit setting. Thus, as an additional check, I rerun all main analyses over a reduced sample that excludes 2007 and all subsequent years, which leaves 100,745 bank-year observations in the sample. Results regarding opacity are qualitatively unchanged. In terms of fragility, results are qualitatively unchanged except for the coefficient on NPL, which is now significantly negative. Since the results are so similar they remain untabulated for brevity.

Although the analysis is dealing with a censored dependent variable, previous studies investigating efficiency measures have used OLS to generate their results (Pi and Timme, 1993). This may be justified on the grounds mentioned by Simar and Wilson (2007), who note that the apparent truncation of efficiency scores may be an artifact of finite samples, and not the true model (p. 40). Therefore, to ensure that the method of estimation is not driving results, I rerun all analyses using a panel data model including fixed effects for banks and years following Pi and Timme (1993) (see Appendix B.2.3). Results are again qualitatively unaffected and, with respect to opacity, slightly stronger. The same is the case if, following Simar and Wilson (2007), I use truncated regression instead (see Appendix B.2.4).

The main motivation for using intermediation quality as dependent variable in the main analysis is the econometric conundrum of investigating relations between an all encompassing balance sheet measure of liquidity creation and balance sheet measures of opacity and fragility. Intermediation quality is introduced to avoid trivial coefficients. However one could also approach the issue from the direction of the independent variables of interest. Specifically, in a separate robustness check, I use various approaches of generating opacity and fragility indices in order to proxy for these features of banks. Concretely I investigate principal components analysis, summation, ranking and average ranks. This allows the analysis to proceed using $CATFAT$ and $CATNONFAT$ liquidity creation as dependent variable directly while reducing the danger of tautological results. This analysis is reported in Section B.2.6. Results are encouraging in that they show that all four opacity and fragility indices are significantly and positively related to liquidity creation. This holds both individually and with opacity and fragility jointly included in the regression specification. Therefore the main results are also robust to this modified approach.

I have also rerun regressions across samples split by bank size in the spirit of Berger and Bouwman (2009) without major qualitative changes to the reported results (see Appendix B.2.5). Thus, overall, findings are extremely robust.

4.7. Conclusion

The regulation of banks in the wake of the financial crisis has been geared towards increasing capital requirements and bank transparency. While more stringent capital requirements have led to a shortage in loan provision, there may be a similar but more latent cost to greater disclosure. The theory provides three distinct hypotheses about the relations between the quality of financial intermediation, fragility and opacity. A first set of theories related to the soft budget constraint literature predicts that opacity will be beneficial because it will exert demand side disciplining pressure on borrowers, while fragility will have the opposite effect. Bank borrowers with bad projects cannot know whether an opaque bank will roll over their project's loan and thus are compelled to expend greater effort, which ultimately leads to better loan portfolios and less fragile banks ("Opacity-Hardness Hypothesis"). A second set of theories indicates that opacity should have a positive influence alongside fragility because it is the threat of a bank run that disciplines banks and induces them to commit full effort to the monitoring of borrowers ("Opacity-Fragility Hypothesis"). A third set of theories predicts that both opacity and fragility should have a negative relation with the quality of financial intermediation. This strand of the literature emphasizes that opaque banks cannot bridge a gap of beliefs existing between optimistic borrowers and pessimistic lenders ("Opacity-Ownership Hypothesis").

I investigate and disentangle these hypotheses using a large sample of the US banking population. To obtain an econometrically efficacious indicator of intermediation quality that will not be trivially associated with available balance sheet opacity and fragility measures, stochastic frontier analysis and generalized frontier analysis and the liquidity creation measures of Berger and Bouwman (2009) are used in order to parametrize a "liquidity frontier". Using the resulting liquidity efficiency scores as a proxy for intermediation quality, this chapter tests the above hypotheses and finds that there is a strong, positive and persistent association between opacity and intermediation quality. Results also provide support for theories that predict that fragility will positively influence the quality of financial intermediation. Furthermore, the effect of opacity and fragility on intermediation quality is at least partly dependent on the opacity of the bank. Intuitively, less opaque banks again benefit more strongly from opacity than do more opaque ones. This finding aligns well with the "Opacity-Fragility Hypothesis". This indicates that the trust problems that both lenders and borrowers will have with respect to a bank are exacerbated by opacity.

The results reported in this chapter hold under a variety of robustness checks. Moreover, they point out interesting directions for future research and highlight important policy implications. First, it would be of considerable interest to see the development of theoretical models of the intermediation process that explicitly incorporate the finding that opacity is a salient feature of this activity. The, as yet unfinished, work of Monnet and Quintin (2013) may indeed be a first step in this direction. Second, from the perspective of the regulator, a certain forbearance with respect to bank opacity may be in order if the goal of high intermediation quality between lenders and borrowers is to be achieved. This could, for example, be accomplished by keeping additional disclosure requirements for banks that fail stress tests confidential etc.

5. Managerial Ability, Liquidity Creation and Risk-Taking

This chapter hypothesizes that more able bank managers create more liquidity and take greater risks. These hypotheses find support in the data. In addition, different strands of the literature disagree on the reaction of bank liquidity creation to crisis shocks. While the empirical literature suggests that increasing liquidity creation improves the competitive position of the bank post crisis, theoretical work indicates that a reduction in liquidity creation may be individually optimal. Therefore, using a difference-in-differences approach, this chapter also studies the impact of pre-crisis managerial ability on the liquidity creation of banks during the financial crisis. Findings indicate that the impact of pre-crisis managerial ability on bank liquidity creation is negative as suspected. Additional findings show that more ably managed banks also reduce risk as a reaction to the crisis.

5.1. Introduction

While the liquidity creation of banks is one of the central services they provide to the economy, it has only recently received attention in the empirical literature (see for example Berger and Bouwman, 2009). Similarly, managerial ability has for a long time been ignored, under the assumption that managers are largely homogeneous entities that follow identical goals. Only recently has this view been challenged by a growing body of literature that recognizes the impact that managers have on firm performance (see for example Bamber, Jiang and Wang, 2010, Bertrand and Schoar, 2003, Demerjian, Lev and McVay, 2012).

Thus, more able managers have, for example, been found to be positively performance relevant in industrial firms (see for example Demerjian, Lev and McVay, 2012) and to report higher quality earnings in banks (see for example Cantrell, 2013). Furthermore, more able managers have been shown to provide their firms with superior reactions to crisis events (Andreou, Ehrlich and Louca, 2013) and to decisively influence firm decisions and governance (Bertrand and Schoar, 2003). Motivated by these results, this chapter hypothesizes that more able managers will run banks that create more liquidity. In addition, this chapter postulates that, because of their superior ability, more able bank managers can and do take more risk. Both of these assertions find support in the data.

A related empirical question of interest is whether more able managers react to shocks by expanding or by contracting the liquidity creation of their banks. Thus, Bebchuk and Goldstein (2011) argue on theoretical grounds that it may be individually optimal for banks to curtail their intermediation activity in the face of shocks to the economy. Naturally, banks led by more able managers should be in a better position to carry out such an adjustment if it is indeed optimal for them to do so. However, Berger and Bouwman (2008) present empirical evidence to the contrary. Their findings suggest that banks may even increase liquidity creation during crises and that such an increase improves these banks' value creation and competitiveness. This in turn provides managerial incentives to expand intermediation activity during crises and it seems reasonable to suppose that more able managers will pursue such a strategy more effectively. This chapter uses a difference-in-differences approach to investigate these conflicting predictions. In so doing it isolates the effect of pre-crisis managerial ability on bank liquidity creation during the recent financial crisis. Results suggest that the impact of pre-crisis managerial ability on liquidity creation is negative during the crisis. This provides support to the theory of Bebchuk and Goldstein (2011). In addition, this chapter posits that more able managers are more effective at de-risking their banks in times of crisis. Using the same identification strategy, I find support for this final prediction. This is consistent with the interpretation of the reduction in liquidity creation as an optimal reaction to the crisis shock.

In brief, this investigation contributes to the understanding of the banking industry in several important ways. First, it provides further insight into bank liquidity creation and risk-taking by showing the importance of managerial ability for these key features of banks. It also provides valuable evidence on the impact of financial crises on bank liquidity creation and risk-taking through the channel of managerial ability. Furthermore, this work extends the analysis of Demerjian, Lev and McVay (2012) by considering various implementations of their managerial ability measure. This not only makes the present analysis robust but also demonstrates the robustness of Demerjian, Lev and McVay's (2012) managerial ability measure.

The rest of this chapter is organized as follows. Section 5.2 reviews the various strands of the literature and develops the hypotheses. Section 5.3 discusses the data and variables used in the investigation. The results of the empirical analysis are reported in Section 5.4 and Section 5.5 discusses various robustness checks. Section 5.6 concludes.

5.2. Review of the Literature

This section discusses the literature that underpins the analysis in this chapter. Firstly, it summarizes the literature related to managerial ability and defines the proxy of managerial ability to be used in this investigation. Secondly, this section discusses liquidity creation of banks and how to measure this important quantity. Thirdly and finally, this discussion motivates predictions about the impact of managerial ability on liquidity creation and risk-taking. Furthermore, it offers an additional set of predictions about the relation between managerial ability and liquidity creation as well as risk-taking in crisis times.

5.2.1. The Importance and Quantification of Managerial Ability

The management literature has long been aware of the importance of the manager, or of the top management team, for the outcomes achieved by the enterprise. This body of research shows, for instance, that the composition of the top management team matters for important strategic decisions such as globalization (Carpenter and Fredrickson, 2001). Furthermore, it has been found that top management team demographics and constructive conflict may be decisive for the success or failure of new technology ventures (Eisenhardt and Schoonhoven, 1990). One theoretical approach, and much of the related literature, that has formalized reasons for the pervasiveness of management factors in driving success is summarized by Hambrick's (2007) upper echelons theory. This theory predicts that the complexity of actual decision making situations necessitates an idiosyncratic importance of managers for industrial outcomes. Specifically, he draws on the seminal work of Hambrick and Mason (1984), in arguing that managers are instrumental in influencing the behavior of the organizations they govern. This is especially believed to be the case if one considers not only the CEO but also the top management team (TMT) as a whole. Strikingly, economics and finance research has been reluctant to abandon the neoclassical paradigm, which leaves limited space for manager idiosyncrasies. Thus, for example, managerial ability has, until recently, been denied existence altogether in the empirical asset pricing literature studying mutual fund performance (Berk and Stanton, 2007). It is therefore not surprising that the banking literature has explored questions related to the behavior of managers largely through a neoclassical lens or, at best, through the lens of agency theory. Although this paradigm relaxes the stringency of the neoclassical view somewhat, it still posits that individuals are more or less homogeneous and merely react rationally to the regulatory and incentive framework they find themselves in (see Bamber, Jiang and Wang, 2010, for further discussion).

However, more recent research has recognized the role of managers more explicitly. Thus, for example, Khanna and Poulsen (1995) show that, while firm distress or failure cannot conclusively be attributed to them, managers do matter for firm performance. Other work has documented even more far reaching and specific influences emanating from the managers to the firm. An important contribution by Bertrand and Schoar (2003) investigates the impact of managerial ability on firm behavior. The authors use manager fixed effects to determine managers' impact on corporate behavior along multiple dimensions such as investment, financing, capital structure and profitability. They find that managers systematically influence their organization's behavior over and above time- and firm-specific characteristics and that these influences can be traced back to demographic properties of managers. They further document that different managers develop distinctive styles of management. Furthermore, Bamber, Jiang and Wang (2010) isolate the effect that an individual manager has on a firm's disclosure policies from the effects of the firm and the environment. Using manager fixed effects, they find that managers contribute substantially to firm disclosure policy and that these effects can be linked to demographic traits of individual managers. Similarly, Rajgopal, Shevlin and Zamora (2006) find that CEO compensation is systematically linked to talent. This indicates that the ability of managers is recognizable to owners, who are willing to remunerate it. Significant effects of managerial influence on accounting behavior of firms have also been documented for CFOs (Ge, Matsumoto and Zhang, 2011). Finally, Leverty and Grace's (2012) work on insurance firms suggests that managers are important and economically significant in terms of influencing firm efficiency. A concept similar to managerial ability (management quality) is explored by Beatty and Liao (2011). Their main objective is the investigation of suspected pro-cyclicality in the generally accepted incurred loss method as applied to loan loss provisions. They find support for the conjecture that more ably managed banks will foresee loan losses earlier and thus recognize these earlier.

So far managerial ability, being latent, has been a challenging concept to operationalize empirically. A main contribution of the body of literature discussed above is that it has developed feasible operationalizations of managerial ability. However, its specific choice of ability measure also represents its greatest limitation. Thus the focus has been primarily on manager fixed effects and, in the case of Rajgopal, Shevlin and Zamora (2006), on manager press visibility and firm performance. Constructing manager fixed effects requires firm and manager observations over time. However, the availability of the required data is limited and favors large firms. The same holds for press visibility, where a substantial bias towards large and listed firms is likely. Furthermore, Bennedsen, Pérez-González and Wolfenzon (2006) investigate the ex-post impact of managers on firms by considering how the death of senior managers or of their family members impacts performance. While this study provides further evidence that managers matter for firm performance, it also highlights another potential problem of manager fixed effects, namely that manager turnovers are frequently endogenous to circumstances that are also otherwise problematic for the firm in question. This casts doubt on the reliability of results obtained from manager fixed effects. In addition, focussing on only the CEO or CFO ignores the fact that it is most probably the top management team as a whole that drives firm outcomes as argued for example in Hambrick (2007). Therefore mainstream research on managerial ability has heretofore been hampered in breadth and accuracy by the lack of a measure of managerial ability that reliably disentangles it from other factors and is readily available for large numbers of firms.

Alternatives to the managerial fixed effects approach have been rather limited. Thus, for instance, Leverty and Grace's (2012) analysis postulates that efficiency can be considered a valid indicator of managerial ability. However, they use as their proxy firm efficiency scores, derived from the common DEA method. Even the authors themselves recognize that it is not only the manager who influences this indicator but also other firm and industry related aspects. A similar criticism can be raised against the work of Barr, Seiford and Siems (1993). The authors use DEA for the quantification of managerial ability in banking. They find that technical efficiency can function as a predictor of bank default (see also Barr and Siems, 1997). However, their method exhibits a number of problems. Firstly, they utilize a highly non-standard definition of bank inputs and outputs for use with DEA, following none of the established approaches (intermediation, production, user-cost or value added). Secondly, similar to Leverty and Grace (2012), they use the raw DEA efficiency score to measure managerial ability. Similarly, Beatty and Liao (2011) argue that past return on assets depends on the ability of management and, hence, should be able to proxy for their closely related management quality concept. While the return on assets of a bank no doubt reflects the overall management quality of the institution, such a definition subsumes many factors that are not attributable to management alone, such as the ability to operate at optimal scale, functional organizational structures, the goodwill of clients that has accrued to the institution over its lifespan etc. Therefore using ROA as a proxy for the ability or quality of management is prone to the same objection made to the approaches of Barr, Seiford and Siems (1993), Barr and Siems (1997) and Leverty and Grace (2012).

It follows from this discussion that any efficiency- or profitability-based measure of managerial ability needs to be purged of any effects that ought to be attributed to the firm. This contribution is made in recent research by Demerjian, Lev and McVay (2012), who construct a broad and reliable measure of managerial ability that can be obtained with relatively frugal data requirements. Specifically, they realize that only the portion of firm efficiency not attributed to firm-specific characteristics ought to be attributed to the manager. Revenue efficiency indicates the ability to generate revenues with a given bundle of inputs and outputs relative to other, similar firms. Thus it necessarily subsumes industry and firm influences. However, a firm's ability to generate revenues is in no small part dependent on the ability of management to, for example, choose and bring to fruition positive NPV projects. Thus, once a revenue efficiency score is in hand, managerial ability can be obtained by purging firm- and industry-specific effects from it statistically. This is achieved by running Tobit regressions of the efficiency scores on characteristics that are assumed to be specific to the firm and outside the manager's influence. Given its wide coverage, this measure lends itself particularly to the study of the US banking industry, where a majority of banks are small, not covered by the financial press and not publicly traded. Therefore this chapter adopts the approach of Demerjian, Lev and McVay (2012) to operationalize managerial ability.

5.2.2. Liquidity Creation

In contrast to managerial ability, bank liquidity creation has never been denied its importance. However, systematic studies of bank liquidity creation have been hampered by the unavailability of a suitable operationalization of this variable. Arguably, one of the first attempts to operationalize liquidity creation was conducted by Deep and Schaefer (2004), who developed a measure for what they call the liquidity transformation gap. This measure of banks' liquidity creation postulates that the intermediation of banks can be captured by the difference between short-term assets and liabilities. They argue that any short-term liabilities that are not matched up by short-term assets are used to finance assets of longer duration. This, on their reading, translates into liquidity creation. However, Berger and Bouwman (2009) note that this measure of liquidity creation is not completely satisfactory. This is, for example, because it ignores the possibility of bank liquidity destruction. Such a constellation could, for instance, obtain if a bank used long term liabilities to finance short term assets. Then it is effectively withdrawing liquidity from the wider economy. Deep and Schaefer's (2004) measure also does not account for the possibility of creating liquidity off the balance sheet or through, for example, transforming medium term liabilities into long term assets etc. Consequently, Berger and Bouwman (2009) develop a variety of broader measures of bank liquidity creation.

The measures of Berger and Bouwman (2009) differ both in terms of scope and construction. The construction criteria are chosen to reflect the effort, duration and cost required to liquidate a given asset or liability in the market. They classify assets and liabilities according to maturity (MAT) as well as according to asset categories (CAT, e.g. loans vs securities etc.). Furthermore, they distinguish between measures in and exclusive of off-balance-sheet items (FAT, $NONFAT$). The classification with respect to maturity is straightforward: shorter maturities require less effort to liquidate. The classification with respect to categories relies on judgement. Thus the authors assert, for instance, that residential real estate loans are likely easier to securitize or sell than, for example, commercial and industrial loans and, therefore, should be considered more liquid. Similar considerations govern the classification of all assets and liabilities. They then assign heuristic weights of 0, $\frac{1}{2}$ or $-\frac{1}{2}$ to each class, according to whether it is deemed to create or destroy liquidity. This heuristic choice of weights reflects the postulate that maximum liquidity of unity should be created or destroyed if a liquid liability is used to create an illiquid asset or vice versa. Semiliquid assets and liabilities are assigned zero weights, presumably so as to err on the side of caution in terms of the classification procedure outlined above.

Berger and Bouwman (2009) go on to show that it is primarily large banks that create liquidity, that liquidity creation is value relevant and that it is sensitive to crises. Berger and Bouwman (2012) provide interesting evidence on the reaction of bank liquidity creation to monetary policy. They find that monetary policy designed to stimulate bank liquidity creation, as represented for example by expansive interest rates, is nearly ineffectual during normal times. This holds particularly for the most liquidity creating banks in their sample. Moreover, in crises the efficacy of such policies is found to be even weaker. This indicates that, as crises hit, managers may disregard incentives provided by monetary policy in favor of keeping their institution viable by whatever means are necessary. Berger and Bouwman (2008) also find that banks that were better capitalized and thus more resilient prior and during financial crises benefitted with respect to their market share in terms of liquidity creation as well as value creation post crisis. In this sense the liquidity creation of banks can be said to reflect managers' trade off between risk and return in a unique way. Thus managers balance profit and wealth maximization objectives against risk. They do so by choosing optimal sources of funding and corresponding allocations for those funds according to the risk-return characteristics of the available assets and liabilities. This process ultimately determines the quantity of liquidity created. Given the greater refinement of their metric compared to Deep and Schaefer's (2004), this chapter adopts the $CATFAT$ measure of Berger and Bouwman (2009) as the key indicator of liquidity creation.[1]

5.2.3. Managerial Ability, Liquidity Creation and Risk

The discussion in Section 5.2.1 has shown that more able managers tend to run more successful, better governed firms (see for example Bertrand and Schoar, 2003, Bamber, Jiang and Wang, 2010 or Ge, Matsumoto and Zhang, 2011). By the same token, banks managed by more able top management teams can also be expected to display a superior performance. As discussed in Section 5.2.2 one key feature of banks is the creation of liquidity by providing intermediation services to the economy. Hence it seems reasonable to suppose that more ably managed banks will also be creating more liquidity. Notice that this hypothesis does not require the assumption that managers explicitly target liquidity creation. It simply relies on the superior funding and allocation choices made by more able managers. This claim has so far not been investigated in the empirical or theoretical literature and immediately motivates the first hypothesis, here stated in alternative form:

A1: Ability-Intermediation Hypothesis*: More ably managed banks create more liquidity.*

A second important question is the impact that more able managers have on bank risk-taking. Intuitively, more able managers should be confident in their ability to take desirable, controlled risk. Hence one might expect that more able managers will be found to take more risk overall. If ability is positively correlated with education, as might reasonably be assumed, this view is supported by the evidence in Bertrand and Schoar (2003), who document that managers who hold MBAs are prone to more risky behavior. This view would also be consistent with the evidence in Beatty and Liao (2011), who show that better managers write down nonperforming loans in a more timely fashion. This suggests that the risk that has been taken by managers of greater ability has been reliably estimated beforehand and need not be hidden from outsiders by, for example, rolling over bad loans (see for example Aghion, Bolton and Fries, 1999,

[1] However, both Berger and Bouwman's (2009) and Deep and Schaefer's (2004) measure is examined for robustness in Appendix 5.

Mitchell, 2001). Moreover, more avid risk-taking by more able managers allows for a more aggressive funding/allocation strategy and therefore is compatible with the first hypothesis. Hence I formulate the second hypothesis, again in alternative form:

A2: Ability-Risk Hypothesis*: More ably managed banks take greater risk.*

Another interesting question relates to the interplay between managerial ability and liquidity creation as well as managerial ability and risk during times of crisis. To form a reasonable prior on the impact that managerial ability is likely to have on liquidity creation in crisis times is not straightforward. On the one hand, the findings of Berger and Bouwman (2008) document that banks' reaction to crises can be to both increase and decrease liquidity creation. In addition, they argue that banks that were well capitalized and expanded their liquidity creation market share during and post crises were able to benefit in terms of value creation. This suggests that there is an incentive for managers to increase liquidity creation during crises in order to take advantage of subsequent value gains. Ceteris paribus, more able managers should be better able to exploit these opportunities. It follows that one ought to expect more ably managed banks to expand liquidity creation during and post crises. On the other hand, the theory of Bebchuk and Goldstein (2011) suggests the opposite. More specifically, in an economy where the success of loans to industrial firms depends on the overall volume of loans extended by banks, it may be individually rational for banks to reduce intermediation activity following a negative shock to the economy. This follows from each bank's expectation that other banks will also curtail their intermediation activity and hence failure rates among industrial firms will be high. The financial crisis would certainly qualify as such a negative shock. Therefore one can argue that it is individually optimal for banks to reduce intermediation activity in this case. Again, more able managers should have been able to react more forcefully in order to protect their banks from risk. Hence the third hypothesis has two elements, here stated in alternative form:

A3a: Ability-Value Hypothesis*: More ably managed banks increase liquidity creation during crisis times.*

A3b: Ability-Risk Aversion Hypothesis*: More ably managed banks decrease liquidity creation during crisis times.*

Finally, crisis events are frequently marked by a flight to quality, and de-leveraging respectively de-risking (see for example Brunnermeier, 2009). This is the natural reaction of a bank to shocks because it serves to protect its valuable charter from the impact of the shock. Again, ceteris paribus, more able managers should be in a better position to actively respond to such a shock. Hence one would expect to observe a more thorough de-risking behavior in more ably managed banks. This motivates the final alternative hypothesis underlying this chapter:

***A4: Ability-Reaction Hypothesis**: More ably managed banks decrease risk during crisis times.*

If managerial ability exerts a significant impact on bank liquidity creation, managerial ability has the potential to act as an important indicator variable for regulators. From the viewpoint of the regulator, distinguishing high and low quality banks will enable her to target intervention efforts more purposefully. Additionally, if managerial ability has a clear relation with risk, it can further inform the prudential supervision of banks. Specifically, this measure allows one to flesh out the "M" component of the CAMELS rating criteria because, as discussed for example in Federal Reserve Bank of San Francisco (1999), this component specifically targets the quality of bank management. In normal times, bank characteristics that are beneficial to liquidity creation can be used to govern the distribution of support such as the injection of subsidized funds to stimulate lending (for a discussion of the UK's funding for lending initiative see for example Nixon, 2013). Moreover, information about factors that facilitate intermediation activity and risk-taking becomes even more valuable in times of crisis. Here the regulator needs to trade off moral hazard concerns and limited funds against the risk of premature liquidation of positive NPV projects by banks and financial contagion between banks. Thus, if managerial ability can predict liquidity creation and risk of banks during crises, one heuristic which the regulator can resort to is to attach some weight to managerial ability when deciding which banks to support and which to allow to fail.

5.3. Data and Variables

Data are obtained from the Call Reports provided by the Chicago Federal Reserve bank starting with the year 1994 and ending in 2010. All data pre-processing is as described in Section 2.3. Data on banks' liquidity creation follows Berger and Bouwman (2009).[2] Hence the selection of control variables also follows these authors. Among the controls several demographic variables on various regional subdivisions such as county-level population, population density and income growth are required. The raw data can be obtained from the Bureau of Economic Analysis (www.bea.gov) and the the Federal Deposit Insurance Corporation (www.fdic.gov) and the bank-level demographic variables are computed as in Section 4.3. Because the regression specifications are in keeping with Berger and Bouwman (2009), the basic setup uses 3-year moving averages

[2] I thank Christa H. Bouwman, who has kindly made the data freely available on her website.

of the regressors to combat endogeneity concerns. Hence the final dataset spans the years 1996-2010 and contains 100,976 bank-year observations. The definition of the financial crisis is also consistent with the literature. While Watts and Zuo (2012) suggest that August 1st 2007 might be a correct starting period, the NBER definition focuses on December 2007. Milestone events that precipitated the crisis started occurring in the summer of 2007 when UBS and Bear Sterns hedgefunds experienced liquidity shortages and the commercial paper market began freezing up (Brunnermeier, 2009). Thus it seems justified to assume that 2006 was the last full year in the sample not affected by the crisis. The end of the crisis is usually dated to mid 2009 (e.g. NBER). Hence the base specification considers 2007-2009 as the crisis years.

The empirical analysis proceeds in three steps, two of these are related to the hypotheses formulated at the outset while one is preliminary. The first, preliminary, step is to compute bank efficiency using data envelopment analysis (DEA), stochastic frontier analysis (SFA) and generalized frontier analysis (GFA). As has been discussed in Sections 2.1.1 and 2.1.2 as well as in Chapter 3, the character of these three methods is different and therefore the information contained in the revenue-efficiency scores obtained from these methods will differ somewhat. Therefore considering all three methods will constitute a valuable robustness check. More specifically, DEA is a deterministic technique. As such it attributes any noise that is contained in the data to (in-)efficiency. SFA does not require the data to be observed without errors. However, it does postulate a functional form that underlies the production process. Although studies have shown that the common parametrizations, such as the Translog, can capture cost and revenue efficiency, such an assumption may prove unjustified in a practical application. GFA is the most general method as it does not impose assumptions of any kind on the data generating process. Because SFA is a well established method in the Banking literature and because it has been shown to be able to parametrize revenue efficiency appropriately, this chapter focuses on SFA as the baseline efficiency measurement method. However, results obtained using GFA and DEA are investigated at length in Appendix C and generally are in line with the main conclusions.

The first step of the actual analysis is to use the approach of Demerjian, Lev and McVay (2012) to purge the efficiency scores of any bank-specific influences that cannot be attributed to the management team. This is accomplished by running a Tobit regression of the efficiency scores on a set of controls. Since prior evidence on the managerial ability of banks is limited, it is necessary to assess the plausibility of the managerial ability scores. This is achieved first, by examining correlations between managerial ability and common bank performance characteristics and, second, by regressing profitability characteristics on managerial ability and a set of controls. The expectation here is that a plausible managerial ability indicator should exhibit positive relevance for profitability. The results show that the MA scores are related to profitability in plausible ways and thereby validate this variable.

The second step constitutes the bulk of the analysis. Specifically, it investigates the influence that managerial ability exerts on liquidity creation and bank risk characteristics during normal (Section 5.4.2) and during crisis times (Section 5.4.3). In considering the financial crisis the analysis follows Duchin, Ozbas and Sensoy (2010) by applying a difference-in-differences approach so as to to isolate the effects of pre-crisis managerial ability on liquidity creation while mitigating endogeneity concerns.

5.4. Empirical Results

This section presents the main results. Specifically, Section 5.4.1 provides evidence on the plausibility of the managerial ability proxy used in this analysis. Section 5.4.2 examines the impact of managerial ability on the liquidity creation and risk-taking behavior of banks. Finally, Section 5.4.3 analyzes the role of managerial ability with respect to bank liquidity creation and risk-taking during the financial crisis.

5.4.1. Obtaining and Validating Managerial Ability

Having obtained the efficiency scores of the banks in question, the next step is to disentangle managerial ability from bank-specific effects. To this end this section follows Demerjian, Lev and McVay (2012). Their approach is to derive a measure of managerial ability from a regression of bank revenue efficiency on a set of bank-specific explanatory variables. They argue that the residual from such a regression captures that component of revenue efficiency, which cannot be explained by the other regressors and thus can be attributed to the manager. Cantrell (2013) shows that this measure has power to explain the quality of reporting in banks. Specifically, he demonstrates that it can explain the relation between actual and predicted fair values of securities and loan losses, as predicted by bank managers. Demerjian, Lev and McVay (2012) further show that the measure is positively correlated with other common metrics that have been proposed to describe managerial ability such as past returns, manager fixed effects, etc.

Therefore this chapter follows the literature in its choice of regressors. Specifically, it includes leverage and the number of employees as recommended by Cantrell (2013) as well as the size of the bank, a dummy variable that indicates free cash flow and the age

Table 5.1.:
Regression Results for Managerial Ability.
Coefficients from yearly Tobit regressions for the year 2004. The dependent variable is the profit efficiency score obtained from data envelopment analysis. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. $BKSIZE$ stands for the natural log of gross total assets, $NUMEMP$ is the natural log of the number of thousand full-time equivalent employees, AGE is the log of bank age, $LEVRAG$ is the leverage of the bank, while FCF is a dummy variable set to one if the bank has free cash flow. Monetary values are in 2005 US Dollars.

$BKSIZE$	0.0677***
	(8.72)
$NUMEMP$	-0.0836***
	(-10.45)
AGE	0.0196***
	(11.64)
$LEVRAG$	0.00387***
	(5.68)
FCF	0.0394***
	(6.45)
Constant	-0.596***
	(-9.04)
N	6505

of the bank following Demerjian, Lev and McVay (2012). In keeping with Demerjian, Lev and McVay (2012), it runs a Tobit regression of efficiency on some bank-specific variables and year fixed effects, while clustering by bank. However, Demerjian, Lev and McVay (2012) run their regressions over a pooled sample of banks. This creates the potential for look-ahead bias in the estimation of managerial ability. Hence this chapter chooses a yearly regression approach. Moreover it is likely that the objective of managers is the maximization of profits rather than revenues. Hence the present approach chooses a broader efficiency measure, namely profit efficiency as the dependent variable in the regression. The residual from this regression constitutes the measure of managerial ability. Concretely, the regression takes the following form:

$$\begin{aligned}\pi - \text{eff}_{DEA,i,t} =& \alpha + \beta_1 \text{BKSIZE}_{i,t} + \beta_2 \text{NUMEMP}_{i,t} + \beta_3 \text{AGE}_{i,t} + \beta_4 \text{LEVRAG}_{i,t} \\ &+ \beta_5 \text{FCF}_{i,t} + MA_{i,t}.\end{aligned} \tag{5.1}$$

Here $\pi - \text{eff}_{DEA,i,t}$ represents profit efficiency as computed by DEA. $BKSIZE$ is the log of gross total assets, $NUMEMP$ is the log of the number of full time equivalent employees in thousands, AGE is the log of the age of the bank in years, $LEVRAG$ represents leverage and FCF is an indicator variable that takes the value one when cash flow for the year is positive. The residual, MA, captures all effects that are specific to the manager and not the bank. Table 5.1 reports the results.

The measure of managerial ability will clearly heavily influence the outcome of the subsequent analysis. Therefore it is important to thoroughly check the robustness of the subsequent results to different specifications of managerial ability. Specifically, the original study by Demerjian, Lev and McVay (2012) assumes that the managerial objective is, in fact, revenue maximization. Furthermore, the approach assumes that the covariates used in the regression from which MA is obtained accurately and exhaustively capture all bank-specific effects that are not attributable to the actions of the manager. Finally, the MA measure can be computed using both pooled as well as yearly data. The robustness checks (5.5) and Section C.1 in the appendix investigate and discuss the implications of various choices for the parametrization of MA at length. Specifically, I compute MA using DEA, SFA and GFA revenue efficiency as well as DEA profit efficiency, using both pooled and yearly regressions and using three different sets of regressors. Overall, this analysis reveals that the specific parametrization of managerial ability is secondary for the general conclusions.

Once the managerial ability measure has been obtained, it is important to investigate its plausibility. To do so I check whether it is value- and performance relevant. I first investigate the correlations between this measure and generic performance indicators.

As performance indicators this chapter uses ROA and ROE and the shareholder value ratio ($SHVR$), which, in the spirit of Cipollini and Fiordelisi (2012), is defined as the quotient between economic value added and gross total assets. These provide first evidence on the value relevance of the managerial ability measure. This analysis also considers how managerial ability is related to the Z-Score ($ZIND$)[3], the three year moving standard deviation of ROA ($SDROA$), the ratio of risk weighted assets over total assets ($CREDRSK$), nonperforming loans (NPL) and tier 1 ratio ($T1R$). These variables capture the association between managerial ability and risk. Results are reported in Table 5.2.

As can be seen from Table 5.2, managerial ability displays a significantly positive, albeit modest, correlation with the value creation characteristics. The correlation is on the order of magnitude reported by Demerjian, Lev and McVay (2012). Evidence on the riskiness characteristics is mixed. Thus it seems that more ably managed banks have smaller variation in return on assets ($SDROA$) and commensurately but insignificantly greater Z-Score and thus less risk ($ZIND$). This may well be grounded in a better skill

[3]Z-Score is computed using the moving standard deviation of return on assets over the last three observations. This chapter, as opposed to Chapter 4, includes only one specification of Z-Score since the subsequent regressions include both the standard deviation of return on assets computed as the moving standard deviation over three observations within one firm. Thus including an alternative parametrization of Z-Score, where the variability of returns is driven by the population of banks would be inconsistent in this setting. One could argue that a pooled approach would provide the benefit of conserving observations. However, this does not hold in the present case since all of the later stage regressors are calculated as moving three year averages and observations with unavailable data are therefore lost regardless of the choice made with respect to Z-Score.

Table 5.2.:
Correlations of Managerial Ability with General Performance Measures.
This table reports Pearson correlation coefficients of managerial ability and bank performance characteristics. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. ROA (ROE) stands for return on assets (equity). $CREDRSK$ is the quantity of risk weighted assets over total assets. $ZIND$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. The corresponding standard deviation of return on assets is given by $SDROA$. $T1R$ stands for the tier 1 ratio, $LAGTA$ stands for liquid assets scaled by total assets. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using DEA-based profit efficiency and regressions across yearly subsamples.

	MA
ROA	0.0498***
ROE	0.0528***
$SHVR$	0.0313***
$CREDRSK$	0.0975***
NPL	0.00422
$T1R$	-0.0295***
$SDROA$	-0.0173***
$ZIND$	0.00251
$LAGTA$	-0.0781***

of more able managers to anticipate and accordingly smooth out earnings, suggested by the negative correlation with volatility of return on assets ($SDROA$). On the other hand, the sum of risk weighted assets scaled by gross total assets ($CREDRSK$) increases in managerial ability, which suggests that these managers run a generally riskier operation. The positive correlation between NPL and MA, albeit insignificant, indicates that the quality of the loan portfolio decreases in managerial ability. Furthermore, the tier 1 ratio ($T1R$) and the quantity of liquid assets ($LAGTA$) is lower for banks that are more ably managed. Thus the bulk of this preliminary evidence points towards more ably managed banks being more profitable and value creating but also more risky.

An ideal additional check on the plausibility of the MA measures would be to consider the alignment of MA scores with CEO tenure and compensation. Specifically one would expect more able managers to be more generously remunerated and remain with a given bank for longer. However, the information that the Call Report provides on the authorized signatory of the report, presumably the CEO or CFO, is confidential and thus not available. Nor does the Call Report provide access to the remuneration of executives. However, an alternative check is available. The literature on managerial ability has so far mainly concentrated on showing the importance of MA for industrial firm performance (Demerjian, Lev and McVay, 2012). Evidence that this measure is appropriate for banks is provided by Cantrell (2013) who shows that the MA measure is indicative of superior reporting quality. However, evidence that Demerjian, Lev and McVay's (2012) measure is significant for bank performance is as yet incomplete. Therefore, as an alternative validation step, I regress ROA and ROE on managerial ability along with the first order lag of MA. If MA is a useful predictor of bank performance, one would expect positive relations with return on assets and return on equity. The specification can be formalized as follows:

$$PM_{j,i,t} = \alpha + \sum_{k=0}^{1} \beta_{k+1} MA_{i,t-k} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{5.2}$$

where PM_j signifies the jth performance measure for $j \in \{ROA, ROE\}$. MA denotes the managerial ability measure. d_t are year dummies and $\mathbf{z}$ is a vector containing control variables. The control variables include the log of gross total assets ($BKSIZE$) to capture differences in profitability due to bank size such as economies of scale, and cost efficiency parametrized by SFA (CE) to capture differences in technology and allocation which may drive profitability. Furthermore, the regression controls for bank holding company status: $MBHC$ ($OBHC$) is a dummy set to one if a bank is part of a multibank (onebank) holding company. It also controls for merger and acquisition activity: MRG (ACQ) is a dummy variable set to 1 if the bank has experienced a merger (acquisition) in the last 3 years. Following Berger and Bouwman (2009), I also obtain a number of variables that cover banks' demographic characteristics. Specifically, the regression controls for bank-level concentration using the Herfindahl index ($BKHHI$). It also controls for bank-level population and population density in the markets it services ($BKPOP$, $BKPDNS$). Furthermore, the performance of banks could depend on the affluence of their markets. Hence the regression introduces the income change of each bank's markets ($BKICHG$) as a control. Finally, competition in a given market is likely a driving factor behind a bank's performance. Therefore the regression controls for the bank-level presence of medium and large banks in the markets it services ($BKMSML$). Bank-level means the weighted average of market-specific values, where a bank's deposits in a given market relative to the bank's total deposits function as weights. For details see Section 4.3.

The results of these regressions are reported in Table 5.3. The coefficients show that for both ROA and ROE, managerial ability has a strongly significant and positive impact, both contemporaneously and in lagged form. This documents that the MA measure can capture bank profitability and, hence, supports its validity. The controls show that size is negatively associated with profitability ($BKSIZE$) as is cost efficiency (CE). Banks that operate in more affluent ($BKICHG$), less densely populated ($BKPOP$, $BKPDNS$) markets with a greater presence of medium and large banks ($BKMSML$) tend to be more profitable. This latter feature may point to the superior

Table 5.3.:
Bank Profitability and Managerial Ability.
This table reports results from fixed effects regressions of return on assets (ROA) and return on equity (ROE) on managerial ability (MA), lagged managerial ability and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$), cost efficiency (CE) and bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using DEA-based profit efficiency and the standard first stage regressors in yearly Tobit regressions.

	ROA	ROE
MA_t	0.00138***	0.0226***
	(3.03)	(2.81)
MA_{t-1}	0.000347	0.00345
	(0.78)	(0.62)
CE	-0.00489***	-0.114***
	(-3.14)	(-6.37)
$BKSIZE$	-0.000668***	-0.0158***
	(-3.32)	(-6.78)
$BKHHI$	0.00110	0.0130
	(1.27)	(1.27)
$BKMSML$	0.00314***	0.0390***
	(7.19)	(7.43)
$BKPOP$	-0.000818***	-0.00900***
	(-5.69)	(-5.33)
$BKPDNS$	-0.00105***	-0.0136***
	(-3.66)	(-3.86)
$BKICHG$	0.0374***	0.485***
	(17.97)	(19.37)
$MBHC$	0.000346	0.0122***
	(1.19)	(3.64)
$OBHC$	0.000603***	0.0139***
	(2.62)	(5.15)
MRG	-0.00255**	-0.0340*
	(-2.24)	(-1.78)
ACQ	-0.000201	-0.00344**
	(-1.57)	(-2.25)
Constant	0.0283***	0.450***
	(9.40)	(12.76)
Bank FE	yes	yes
Time FE	yes	yes
Adj. R^2	0.153	0.154
N	84356	84356

ability of larger institutions to identify more attractive markets. Apparently, this effect overcompensates any detrimental influence of greater competition exerted by these institutions in such markets. Bank holding companies are more profitable than non-bank holding companies ($MBHC$, $OBHC$). Recent mergers and acquisitions impair profitability (MRG, ACQ). This may be due to integration costs that are incurred before the benefits of economies of scale and scope due to mergers or acquisitions can be fully realized. Overall, the control variables provide plausible information; but more importantly, the regressions confirm the expected positive relation between managerial ability and profitability and thus validate the MA measure.

5.4.2. Managerial Ability, Liquidity Creation and Risk-Taking

This section analyzes the relation between managerial ability and bank performance in normal times. Liquidity creation is addressed first. Subsequently, this section also investigates bank risk along a number of dimensions.

In line with Berger and Bouwman (2009), this section analyzes liquidity creation using data that is stratified by bank size. It is well known (see e.g. Feng and Serletis, 2009) that the US banking industry is composed of a large number of small banks and substantially smaller numbers of medium and very large banks. Accordingly, this chapter uses cutoffs at 1bn USD and 3bn USD to separate small, medium and large banks and runs the analysis for each subsample of the population separately as well as for the full sample of banks.

Table 5.4 reports summary statistics for the main variables of interest. The measure of managerial ability (MA) shows that large banks have greater managerial ability than other banks but also that the variation in managerial ability among large banks is greatest among the three subsamples. Since MA is constructed as a residual, it is natural to observe that for the full sample managerial ability is close to zero on average. Consistent with findings in Berger and Bouwman (2009), liquidity creation relative to total assets ($CATFAT$) is much greater in large banks. Also, the numerical values match up well with theirs especially if one takes into account the difference in time period. Large banks also exhibit lower levels of nonperforming loans (NPL) and tier 1 capital ($T1R$). They also have greater quantities of risk weighted assets on their books ($CREDRSK$). They usually are more risky in terms of distance to default as well, while the variation of return on assets also tends to be greater ($ZIND$, $SDROA$). Medium and large banks tend to be more cost efficient than small banks (CE) and they operate in more populous, affluent and less concentrated markets ($BKPOP$, $BKPDNS$, $BKICHG$, $BKHHI$). Medium banks also exhibit the highest merger and acquisition activity in the sample ($MRG\ ACQ$) as well as the lowest level of liquid assets ($LAGTA$). Overall, the characteristics of the sample are in line with those reported by Berger and Bouwman (2009). The only distinctly different values appear for the merger and acquisition dummies. It is likely that this difference results from the different time periods examined.

Next, this section investigates bank liquidity creation in more detail in order to test A1, the hypothesis that more ably managed banks create more liquidity. The specification is a fixed effects regression using bank and year fixed effects and computing

Table 5.4.: Summary Statistics.

$BKSIZE$ stands for the log of gross total assets, CE is cost efficiency parametrized by way of SFA. NPL represents the ratio of nonperforming loans to total loans. $T1R$ is the tier 1 ratio. $CREDRSK$ is the ratio of risk weighted assets and total assets. $ZIND$ represents the Z-Score computed using the three year moving standard deviation of ROA. $SDROA$ is the three year moving standard deviation of ROA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $CATFAT$ is the liquidity creation measure of Berger and Bouwman (2009) including off-balance-sheet items. MA is managerial ability parametrized by applying the method of Demerjian, Lev and McVay (2012) to DEA-based profit efficiency on yearly subsamples.

	Panel A: Small Banks		*Panel B: Medium Banks*		*Panel C: Large Banks*		*Panel D: All Banks*	
Parameter	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)
MA	0.0051537	0.0691925	0.0041217	0.0937322	0.0560356	0.1296798	0.0062493	0.0725381
$CATFAT$	0.2609532	0.1704291	0.3772222	0.162688	0.4006081	0.1750225	0.26842	0.1728281
NPL	0.0131684	0.0154775	0.0136227	0.017093	0.0125262	0.0152316	0.0131711	0.015536
$T1R$	0.1548701	0.0654793	0.1175263	0.0363189	0.1087706	0.0368406	0.1524441	0.064844
$LAGTA$	0.3573056	0.1435347	0.3198673	0.1260164	0.355771	0.1347142	0.3558695	0.1429014
EA	0.1014051	0.0294536	0.0927119	0.0260902	0.0922414	0.0304706	0.1008753	0.0294326
$CREDRSK$	0.6651933	0.1219095	0.7195732	0.1190108	0.7300493	0.1342354	0.6686753	0.1228748
$BKSIZE$	11.59481	0.9467878	14.26992	0.3092754	15.64986	0.3871035	11.78538	1.203325
CE	0.9248182	0.0393343	0.9501846	0.0385127	0.9454771	0.0555679	0.9262286	0.0401337
$BKHHI$	0.233499	0.1479367	0.1869667	0.0920543	0.1894593	0.0883459	0.2307754	0.1455544
$BKMSML$	0.4104661	0.3085378	0.7409172	0.1633227	0.7745536	0.1820533	0.430952	0.3128411
$BKPOP$	12.14878	2.315391	14.24668	1.60061	14.77175	1.320667	12.28578	2.339856
$BKPDNS$	2.912769	0.9235044	3.212207	0.7738622	3.337604	0.6793655	2.933448	0.9173717
$BKICHG$	0.0474976	0.0428796	0.0452483	0.03449	0.0504401	0.0305241	0.0474789	0.0423616
$SDROA$	0.2643613	0.3360031	0.3031487	0.4730333	0.3034995	0.4274351	0.2666862	0.344509
$ZIND$	1.076425	1.340253	1.114503	1.39186	0.9384543	1.20451	1.074758	1.33951
$MBHC$	0.2241532	0.4170256	0.4078286	0.491496	0.6472679	0.4779264	0.2404631	0.4273668
$OBHC$	0.5770875	0.4940244	0.497223	0.5000584	0.3007552	0.4586883	0.5679369	0.4953655
MRG	0.0000948	0.0097357	0.0015869	0.0398093	0.0013327	0.0364905	0.0001783	0.0133503
ACQ	0.0722321	0.2588731	0.0761703	0.2653055	0.0675255	0.2509857	0.0722746	0.2589433
N	94944		3781		2251		100976	

standard errors clustered by bank. Specifically,

$$\frac{CATFAT_{i,t}}{GTA_{i,t}} = \alpha + \beta_1 MA_{i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{5.3}$$

where $CATFAT$ is the liquidity creation measure as defined by Berger and Bouwman (2009) and GTA represents gross total assets. The main variable of interest, MA, is lagged by one period so as to avoid possible endogeneity issues. $\mathbf{z}$ is a vector of control variables. This approach again follows the specification in Berger and Bouwman (2009) and uses as regressors three year moving averages of the sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the moving standard deviation of the ROA ($SDROA$) and the Z-Score ($ZIND$) to capture risk.[4] I further use the log of gross total assets to control for bank size ($BKSIZE$). The regression also controls for organizational characteristics such as holding company status and recent mergers and acquisitions as before. In addition, the regression controls for local market characteristics as defined above. While this section essentially follows the research design of Berger and Bouwman (2009), it deviates from their approach in that it does not include the equity over asset ratio (EA). This is because in their analysis they extensively discuss, highlight and address the possible problems of endogeneity between the EA ratio and liquidity creation. I avoid this conundrum by omitting this variable all together. I investigate the impact of this choice on results in the appendix (Section C.2.3) and find that this does not drive the findings. If A1 holds, one would expect a positive association between managerial ability and liquidity creation. Table 5.5 reports the results of the regression analysis, where each subsample of the bank population is treated in a separate column.

[4]Since these variables all measure risk, the last two are orthogonalized by regressing $ZIND$ and $SDROA$ on each other, $CREDRSK$ and all other explanatory variables and using the resulting errors as the eventual independent variable. Orthogonalizing these measures against one another and the remaining covariates, ensures that the impact of collinearity is minimized and that the orthogonalized variables capture only the dimension not covered by the other variables. Moreover, this procedure ensures comparability of the present results with those provided in Berger and Bouwman (2009) who introduce this regression specification.

Table 5.5.:
Bank Liquidity Creation and Managerial Ability, MA Based on DEA Profit Efficiency.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

Parameter	Small	Medium	Large	Full
MA_{t-1}	0.0136**	0.0511**	-0.0220	0.0114*
	(1.99)	(2.27)	(-0.64)	(1.69)
$CREDRSK$	0.621***	0.675***	0.826***	0.628***
	(55.42)	(14.36)	(10.99)	(57.70)
$ZIND$	-0.000948***	-0.00199	0.00148	-0.000762**
	(-2.79)	(-1.47)	(0.59)	(-2.33)
$SDROA$	-0.00704***	-0.0315***	-0.0324**	-0.00944***
	(-3.11)	(-4.14)	(-2.06)	(-4.36)
$BKSIZE$	-0.0114***	-0.0174	0.00302	-0.0127***
	(-4.52)	(-1.56)	(0.22)	(-5.55)
$BKHHI$	0.0157**	-0.0254	0.0159	0.0124
	(1.98)	(-0.45)	(0.10)	(1.52)
$BKMSML$	0.0195***	-0.00371	-0.0927	0.0174***
	(4.35)	(-0.14)	(-1.61)	(4.00)
$BKPOP$	0.00764***	0.0220***	0.0251	0.00829***
	(4.54)	(2.59)	(1.49)	(5.15)
$BKPDNS$	0.000321	-0.0188	-0.0107	-0.00185
	(0.09)	(-1.36)	(-0.28)	(-0.54)
$BKICHG$	0.202***	0.539***	0.650**	0.222***
	(10.72)	(4.44)	(2.00)	(11.85)
$MBHC$	0.0192***	0.0132	0.0285	0.0193***
	(5.22)	(0.82)	(0.66)	(5.51)
$OBHC$	0.0158***	0.0206	0.0365	0.0166***
	(5.45)	(1.36)	(0.86)	(5.86)
MRG	0.0217	0.0785***	0.0293*	0.0529***
	(1.15)	(4.76)	(1.90)	(4.76)
ACQ	-0.000539	0.00355	-0.00773	-0.000761
	(-0.35)	(0.48)	(-0.62)	(-0.50)
Constant	-0.114***	-0.118	-0.390	-0.1000***
	(-3.40)	(-0.60)	(-1.41)	(-3.24)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.473	0.460	0.376	0.470
N	79152	3341	1863	84356

The main result relates to managerial ability (MA). Importantly, I find that managerial ability is significantly positively associated with liquidity creation for small and medium banks as well as the full bank population. This is as initially hypothesized and suggests that hypothesis A1 should be accepted. In addition, the findings on the control variables are very similar to those reported in the literature. Thus, in keeping with Berger and Bouwman (2009), results show that Z-Score is negatively associated with liquidity creation for small banks ($ZIND$). While they find a significantly positive association for large banks, the coefficient in the present analysis, while also positive, is insignificant. Similarly, the volatility of ROA is negative for all subsamples of banks ($SDROA$). Berger and Bouwman (2009) find a negative association for $CREDRSK$ for small banks and a positive one for medium sized banks. In this sample $CREDRSK$ is positively associated with liquidity creation throughout. While in their sample, the size of the bank ($BKSIZE$) is weakly significantly positive for medium banks and insignificantly negative otherwise, I find significantly negative relations for the medium bank subsample and insignificant relations otherwise. Similar to their findings, being a bank holding company ($MBHC, OBHC$) is beneficial for liquidity creation in small banks. This is likely due to better access to resources channelled through the holding company. In their sample, bank merger activity is significantly positive only for small banks, while in the present sample this association holds also for medium banks and the full sample (MRG). Acquisitions are insignificant in my sample as opposed to theirs, where a significantly positive relation obtains for small banks and a significantly negative one holds for medium banks. Where bank demographics are concerned, the results show that small banks that are active in markets with more medium and large banks ($BKMSML$), more populous ($BKPOP$) and affluent ($BKICHG$) markets create more liquidity. The latter finding is highly significant for medium banks in the present sample as well. Population density is insignificant in the present analysis ($BKPDNS$). Overall, these findings are similar to those in Berger and Bouwman (2009). I attribute any remaining differences to the different time periods covered by the two samples as well as the exclusion of EA and the inclusion of MA_{t-1} in the present analysis.

Naturally, one would assume that managerial ability will have an influence on a number of important bank characteristics, especially risk. Specifically, A2 posits that more able managers will take more risk, perhaps, for instance, due to their greater confidence in their ability to manage such risk. If so, this would be an important feature of banks, which has heretofore not been examined. Hence the following analysis studies these aspects of bank performance by regressing proxies for risk on the usual control variables as well as managerial ability. As risk proxies I choose the ratio between nonperforming loans and total loans (NPL), the tier 1 ratio ($T1R$) and the ratio of liquid assets to total assets ($LAGTA$). The choice of risk proxies is motivated by their ability to capture three important dimensions of bank operations. First, nonperforming loans capture the quality of the loan portfolio, which is a core function of banks. Second, the tier 1 ratio is a key regulatory measure of capitalization, which banks are likely to target in their decision making more strongly than, for example, the equity over asset ratio. Third, the quantity of liquid assets captures the liquidity of a bank, which is a key dimension of it's resilience to shocks. This quantity is defined by using the CAT classification approach of Berger and Bouwman (2009) and considering only liquid assets.

If hypothesis A2 holds, I therefore expect a positive association between managerial ability and NPL and a negative association between managerial ability and $T1R$ and $LAGTA$. The regressions take the form in 5.4:

$$KRI_{k,i,t} = \alpha + \beta_1 MA_{i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{5.4}$$

where KRI_k represents the key risk indicator where k indexes into $\{NPL, T1R, LAGTA\}$. All other regressors are as previously defined. Table 5.6 reports the results.

Again, the focus is on managerial ability. Panel A reports results regarding the quality of the loan portfolio as measured by nonperforming loans. Nonperforming loans are mostly insignificantly negatively associated with managerial ability except for medium banks where the coefficient is significant. Panel B considers the tier 1 ratio. It seems that more able managers prefer to hold substantially lower levels of tier 1 capital. This finding is significant for small banks and present but insignificant for the full sample. Finally, Panel C shows that managers of small banks and banks overall (and insignificantly also medium banks) prefer to hold lower quantities of liquid assets. Overall these findings point to an acceptance of A2: more able managers seem to take greater risk.

In terms of the other covariates, I find that greater holdings of risk weighted assets per unit assets ($CREDRSK$) tend to be negatively associated with capitalization and positively associated with nonperforming loans. Both results are intuitive. Thus one would expect greater quantities of risk weighted assets to coincide with more nonperforming loans. On the other hand, greater quantities of risk weighted assets relative to unit assets implies that fewer assets will qualify for tier 1 capital respectively will be held in short term, riskless, liquid assets. This is consistent with the finding that bank capitalization and, for small banks, also liquid assets decreases with size ($BKSIZE$, Panel B & C). However, larger banks also prefer to hold more nonperforming loans ($BKSIZE$, Panel A). Furthermore, banks with greater quantities of nonperforming loans tend to have more volatile ROA and lower Z-Score, which indicates that NPL is positively associated with risk. Conversely, the opposite relation holds for $T1R$ and $LAGTA$. In terms of demographics, being present in markets that are serviced by medium and large banks ($BKMSML$) and more affluent ($BKICHG$) tends to reduce nonperforming loans, while operating in more populous and less affluent markets ($BKPOP$, $BKPDNS$) has the opposite effect for small banks. All of these results are intuitive. Thus less affluent borrowers tend to default more easily, more densely populated markets tend to be cities, where anonymity reduces moral pressure to repay loans and a greater population overall increases the potential for awarding loans, some of which will likely be nonperforming in the future. Bank holding companies also tend to be more aggressively capitalized and hold less liquidity as is indicated by the negative coefficients on $OBHC$, $MBHC$ in Panels B and C.

Table 5.6.: Bank Risk-Taking and Managerial Ability, MA Based on DEA Profit Efficiency.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MA_{t-1}	-0.000911	-0.0123***	-0.00311	-0.00146	-0.00845***	0.0166	0.00811	-0.00316	-0.0673***	-0.0379	0.0257	-0.0547***
	(-0.81)	(-3.12)	(-0.54)	(-1.35)	(-3.08)	(1.53)	(1.18)	(-1.23)	(-10.59)	(-1.60)	(0.76)	(-8.77)
$CREDRSK$	0.0201***	0.0153**	0.0264***	0.0199***	-0.212***	-0.0900***	-0.0861***	-0.205***	-0.649***	-0.617***	-0.633***	-0.652***
	(15.84)	(2.29)	(3.05)	(16.23)	(-47.50)	(-6.50)	(-5.18)	(-47.72)	(-58.18)	(-13.04)	(-11.50)	(-60.87)
$ZIND$	-0.000440***	-0.0000494	-0.000422	-0.000409***	0.000632***	0.000256	0.0000544	0.000572***	0.000399	0.00206	0.00148	0.000279
	(-7.83)	(-0.23)	(-0.94)	(-7.44)	(3.69)	(0.48)	(0.08)	(3.50)	(1.19)	(1.64)	(0.90)	(0.87)
$SDROA$	0.0124***	0.0162***	0.0221***	0.0129***	-0.00786***	0.00145	0.00307	-0.00614***	0.00797***	0.0186***	0.000500	0.00916***
	(20.12)	(7.72)	(6.19)	(22.30)	(-7.47)	(0.37)	(0.77)	(-6.16)	(3.78)	(2.87)	(0.03)	(4.64)
$BKSIZE$	0.00490***	0.00526***	0.00171	0.00459***	-0.00466***	-0.00193	-0.00810***	-0.00250**	0.00510**	-0.00254	0.0180*	0.00803***
	(10.82)	(3.12)	(0.89)	(11.78)	(-3.70)	(-0.36)	(-2.73)	(-2.35)	(2.27)	(-0.29)	(1.70)	(4.06)
$BKHHI$	-0.00203	-0.00774	0.00139	-0.00212	-0.00354	-0.0190	0.0347	-0.00166	0.00600	-0.0545	-0.0757	0.0101
	(-1.25)	(-0.70)	(0.13)	(-1.34)	(-0.85)	(-0.69)	(0.90)	(-0.40)	(0.75)	(-1.11)	(-0.58)	(1.27)
$BKMSML$	-0.00593***	0.00196	-0.00757	-0.00551***	-0.000869	0.0191	0.0161	0.000853	-0.0153***	0.0200	0.0398	-0.0112***
	(-6.68)	(0.46)	(-0.90)	(-6.41)	(-0.38)	(1.45)	(1.56)	(0.40)	(-3.50)	(0.90)	(0.89)	(-2.67)
$BKPOP$	0.000903***	-0.000647	-0.00208	0.000833***	0.000279	-0.00274	0.000139	-0.0000727	-0.00472***	-0.00282	0.00683	-0.00450***
	(3.19)	(-0.43)	(-1.48)	(3.03)	(0.38)	(-0.74)	(0.06)	(-0.11)	(-3.11)	(-0.37)	(0.53)	(-3.09)
$BKPDNS$	0.00168***	0.00221	-0.00511*	0.00131**	0.000625	0.0179**	0.00452	0.00213	-0.0000131	0.00326	0.0165	0.00222
	(2.78)	(0.83)	(-1.79)	(2.28)	(0.31)	(2.18)	(0.72)	(1.15)	(-0.00)	(0.27)	(0.55)	(0.67)
$BKICHG$	-0.0849***	-0.128***	-0.0422	-0.0889***	-0.0631***	-0.0973	-0.0318	-0.0699***	0.0202	-0.158	-0.204	0.0100
	(-21.97)	(-4.43)	(-1.07)	(-23.59)	(-7.54)	(-1.43)	(-0.41)	(-8.44)	(1.17)	(-1.43)	(-0.82)	(0.59)
$MBHC$	0.000558	0.0000338	-0.00150	0.000464	-0.0176***	-0.00586	-0.0363**	-0.0177***	-0.00970***	-0.00573	-0.0362	-0.0115***
	(1.02)	(0.01)	(-0.47)	(0.89)	(-9.15)	(-0.89)	(-2.17)	(-9.77)	(-2.86)	(-0.35)	(-1.19)	(-3.55)
$OBHC$	-0.000166	0.000171	-0.00155	-0.000189	-0.0123***	-0.00731	-0.0358**	-0.0132***	-0.0142***	-0.0110	-0.0397	-0.0159***
	(-0.36)	(0.06)	(-0.58)	(-0.42)	(-7.66)	(-1.15)	(-2.11)	(-8.48)	(-5.17)	(-0.69)	(-1.36)	(-5.91)
MRG	0.000750	-0.0118***	-0.000896	0.00172***	0.0257***	-0.000934	-0.00375	0.0134	0.0310	-0.0261*	-0.0226*	-0.0163
	(1.05)	(-4.03)	(-0.67)	(3.72)	(7.95)	(-0.16)	(-1.44)	(1.64)	(0.78)	(-1.89)	(-1.88)	(-0.76)

Continued on next page

Table 5.6 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
ACQ	-0.000306	0.000967	0.000271	-0.000238	0.000449	-0.00186	-0.00112	0.000309	0.000940	-0.0155**	0.00449	0.000970
	(-1.25)	(0.87)	(0.18)	(-1.02)	(0.62)	(-0.78)	(-0.40)	(0.45)	(0.65)	(-2.27)	(0.50)	(0.69)
Constant	-0.0577***	-0.0539*	0.0228	-0.0526***	0.360***	0.200***	0.275***	0.329***	0.818***	0.874***	0.240	0.776***
	(-10.05)	(-1.84)	(0.69)	(-10.12)	(23.84)	(2.66)	(5.20)	(24.99)	(28.00)	(4.70)	(1.12)	(28.76)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.312	0.491	0.516	0.325	0.235	0.132	0.181	0.224	0.365	0.357	0.281	0.362
N	79152	3341	1863	84356	79152	3341	1863	84356	79152	3341	1863	84356

Overall, this section provides support for the hypothesis that more able bank managers generally contribute positively to liquidity creation in the economy during normal times. Furthermore, as the split sample analysis shows, this finding is not driven merely by larger banks that may pay more. Managerial ability matters for small banks' liquidity creation as well. In addition, results suggest that more able bank managers tend to pursue more risky strategies in terms of liquidity and capitalization while eschewing loan portfolio risk. The next section addresses the question how managerial ability influences liquidity creation during crisis times.

5.4.3. Effects of Managerial Ability on Liquidity Creation and Risk-Taking During the Crisis

This section investigates the third and fourth hypotheses, namely it asks how the ability of bank management influences the liquidity creation of banks as well as their risk during crisis times.

Duchin, Ozbas and Sensoy (2010) study the impact of the pre-crisis cash holdings of industrial firms on firm investment in response to the financial crisis. They stress that potential endogeneity may confound an investigation such as this. Endogeneity in their setting can arise if the firms' asset structure covaries with the latent investment opportunities open to these firms. In the present setting endogeneity seems much less likely. For endogeneity to arise there would have to exist simultaneous determination of contemporaneous liquidity creation and lagged managerial ability. However, while it is difficult to imagine that managerial ability depends on liquidity creation in some way, it seems very reasonable to posit the reverse. In addition, if one investigates the financial crisis, it seems plausible to assert that managerial ability is predetermined with respect to the crisis. One could argue that owners, anticipating a crisis, may have tried to hire more able managers in the last minute. However, the market for managerial talent is limited and therefore, even if such a behavior were to obtain, it can only affect a very small fraction of the sample of banks. This is especially the case because the majority of the sample consists of small banks where the mobility of managers in terms of their workplace as well as their visibility to competitors is much smaller than, for example, in listed banks where news coverage and disclosure make for much more visible managers. More importantly, given the time needed to decide to replace, to find and to actually recruit a top management team, it seems extremely unlikely that owners will have been able to replace their banks' management in anticipation of an impending crisis event. Moreover, the fact that very few banks actually benefitted from bets against the securitized mortgage market indicates that such foresight did not prevail in broad strata of the market. It is, of course, conceivable that a number of managers were simply fired and replaced with internal successors as a reaction to the crisis. This may have occurred under pressure from regulators or owners as a short-circuit reaction to the onset of the financial crisis. While this is not the same as the time consuming external replacement of the entire top management team, it would nonetheless constitute a source of endogeneity. This, however, can be controlled for by excluding contemporaneous managerial ability from the regressions and focusing only on pre-crisis MA. This thesis achieves an additional mitigation of endogeneity concerns by following the difference-in-differences approach of Duchin, Ozbas and Sensoy (2010). Specifically, to disentangle A3a from A3b I regress the creation of liquidity on an indicator set to one if the respective year is a crisis year and pre-crisis MA interacted with the crisis dummy as well as control variables. This approach isolates the effect of pre-crisis managerial ability on performance during the crisis.

This section considers the financial crisis as encompassing the years 2007-2009. Duchin, Ozbas and Sensoy (2010) study the impact of pre-crisis financial positions on crisis investment opportunities. Their main interest is the supply side effect of the crisis, hence they distinguish two sub-periods within the 2007-2009 timeframe. Since the focus in the present context is on the shock's effect on banks' liquidity creation mediated by pre-crisis managerial ability, it seems unnecessary to distinguish between supply- and demand-side periods as they do. Rather I allow the sample to encompass the main period of financial turmoil 2007-2009.[5] The specification runs as follows:

$$\frac{CATFAT_{i,t}}{GTA_{i,t}} = \alpha + \beta_1 \delta_c + \beta_2 MA_{i,06} \times \delta_c + \boldsymbol{\xi}' \mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}. \tag{5.5}$$

Here δ_c is a dummy variable set to 1 if the year in question falls into the interval 2007-2009. $MA_{i,06}$ is MA parametrized by DEA profit efficiency as measured at the end of 2006. All other variables are as above.

I expect that the crisis dummy should enter with a strongly significant negative sign because of the disruptive effects that the financial crisis had on bank intermediation. The coefficient that is observed on the interaction term will allow one to disentangle

[5] Robustness checks that let the crisis range from 2007-2008 or 2008-2009 show that the main effects that support Bebchuk and Goldstein's (2011) hypothesis emanate from the early portion of the crisis (2007-2008), while the latter part of the crisis in fact associates greater intermediation activity with more able managers. Not only do these results conform with one's expectations, but also do they serve to explain the low significance of the coefficients of interest in the main analysis. (see Appendix C.2.5).

alternative A3a from alternative A3b. Specifically, this regression asks the question whether value orientation motivated managers to extend intermediation during the crisis consistent with Berger and Bouwman (2008) and A3a or whether anticipation of risk led them to reduce it consistent with Bebchuk and Goldstein (2011) and A3b. The results of this analysis are reported in Table 5.7.

Table 5.7.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, MA Based on DEA Profit Efficiency.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

Parameter	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	0.00653	-0.0592	-0.0697	-0.00757
	(0.56)	(-1.41)	(-1.44)	(-0.68)
δ_c	-0.00531***	-0.00733*	-0.0106	-0.00648***
	(-6.16)	(-1.82)	(-1.57)	(-7.74)
$CREDRSK$	0.774***	0.724***	0.769***	0.779***
	(29.80)	(6.88)	(4.28)	(31.05)
$ZIND$	0.00164***	0.00260	0.00542	0.00158***
	(2.72)	(0.96)	(1.04)	(2.70)
$SDROA$	-0.0233***	-0.0343***	-0.0321*	-0.0246***
	(-6.31)	(-4.02)	(-1.97)	(-7.32)
$BKSIZE$	-0.0626***	-0.0271	-0.0196	-0.0531***
	(-8.87)	(-1.12)	(-1.16)	(-8.62)
$BKHHI$	-0.00263	-0.134**	-0.404***	-0.0186
	(-0.21)	(-2.41)	(-3.30)	(-1.51)
$BKMSML$	0.0351***	0.106***	0.0653	0.0363***
	(5.25)	(2.68)	(0.58)	(5.59)
$BKPOP$	0.00351	0.00634	-0.0216	0.00265
	(1.18)	(0.57)	(-0.60)	(0.94)
$BKPDNS$	-0.0210***	-0.0453*	-0.00432	-0.0247***
	(-3.30)	(-1.78)	(-0.07)	(-3.98)
$BKICHG$	0.213***	0.554***	0.401	0.250***
	(10.08)	(4.35)	(1.46)	(12.05)
$MBHC$	0.000770	0.0256	0.0587	0.00247
	(0.11)	(1.10)	(1.54)	(0.36)
$OBHC$	0.00311	0.0346	0.0396	0.00399
	(0.53)	(1.56)	(1.27)	(0.70)
MRG	0	0.0765***	0	0.0843***
	(.)	(4.62)	(.)	(15.75)
ACQ	0.00559*	-0.0235	-0.0320	0.00422
	(1.67)	(-1.13)	(-0.89)	(1.26)
Constant	0.495***	0.219	0.471	0.419***
	(5.78)	(0.71)	(1.05)	(5.45)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.225	0.310	0.317	0.230
N	19793	1059	529	21381

As expected, results show that the crisis has a strongly significant negative impact on liquidity creation (δ_c). Furthermore, the main variable of interest, the interaction of pre-crisis MA with the crisis dummy, $MA_{06} \times \delta_c$, indicates that banks reduced liquidity creation consistent with A3b. However this finding is insignificant. Yet, when one considers multiple parametrizations of MA, as is done in the appendix (see Appendix C.1.4.1), results show that the impact that MA has on liquidity creation is strongly significantly negative during the crisis and much greater than the mere effect of the crisis alone. This indicates that more able managers reduced the liquidity creation of their banks more forcefully, which is in keeping with hypothesis A3b.

The other regressors provide reasonable coefficients. Thus, while increasing levels of risk weighted assets is still beneficial for liquidity creation ($CREDRSK$), it is banks with greater Z-Scores and lower volatility of ROA that create more liquidity ($ZIND$, $SDROA$). This aligns with the flight to quality that is known to have taken place during the financial crisis. In addition, the positive impact of $CREDRSK$ remains because risk weighted assets constitute a substantial portion of overall intermediation volume on the asset side. Within the small bank stratum, larger banks produce less liquidity ($BKSIZE$). Merger activity is recorded only for medium banks during this period and hence omitted in the small and large bank subsamples. For medium banks it has a positive effect on liquidity creation. The demographic variables change in some important respects relative to the main analysis. Thus the presence of medium and large banks in banking markets still catalyzes liquidity creation for small, medium banks and the full sample ($BKMSML$). However, more concentrated markets significantly reduce liquidity creation in medium and large banks ($BKHHI$). This is consistent with possibly prevailing contagion and more aggressive strategies in more concentrated markets. Previously significant $BKPOP$ has lost significance, while the previously insignificantly negative $BKPDNS$ has become significant for small and medium banks as well as overall. This suggests that liquidity creation contracted more in more densely populated markets. Bank holding companies are still more robust liquidity creators than non-bank holding companies ($OBHC$, $MBHC$) but insignificantly so.

Next, in order to investigate the fourth hypothesis, I consider the behavior of key risk indicators during the crisis. Concretely, A4 posits that more ably managed banks were better able to react to the crisis shock by reducing the risk exposure of their operations. The preceding analyses have shown that, during normal times, more able managers tend to prefer running more risky banks in terms of capitalization ($T1R$) and liquidity ($LAGTA$). If more able managers have indeed taken more controlled risks in normal times, they should be more successful in de-risking during the crisis. Therefore, if A4 holds, I would expect a negative sign on NPL and positive signs on $T1R$ and $LAGTA$. The following analysis considers the results during crisis times by running the following regression:

$$KRI_{k,i,t} = \alpha + \beta_1 \delta_c + \beta_2 MA_{i,06} \times \delta_c + \boldsymbol{\xi}' \mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}, \quad (5.6)$$

where again KRI_k represents the key risk indicator with $k \in \{NPL, T1R, LAGTA\}$. All other regressors are as previously defined. Table 5.8 reports the results.

Table 5.8.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, MA Based on DEA Profit Efficiency.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0198***	-0.00599	0.00918	-0.0143***	0.00305	0.0207**	-0.00338	0.00314	0.0334***	0.0314	0.0106	0.0326***
	(-6.64)	(-0.62)	(0.95)	(-5.15)	(0.80)	(2.24)	(-0.33)	(0.91)	(3.15)	(1.33)	(0.30)	(3.37)
δ_c	0.00590***	0.00823***	0.00902***	0.00660***	-0.000440	-0.000540	-0.00246	-0.000439	0.00495***	0.00364	0.00150	0.00534***
	(24.34)	(6.57)	(6.32)	(28.30)	(-1.34)	(-0.46)	(-1.08)	(-1.43)	(6.12)	(1.29)	(0.27)	(6.96)
$CREDRSK$	0.0519***	0.0412	0.0738**	0.0501***	-0.212***	-0.102***	-0.0831**	-0.206***	-0.841***	-0.817***	-0.647***	-0.847***
	(9.30)	(1.43)	(2.20)	(9.25)	(-22.81)	(-3.14)	(-2.47)	(-23.39)	(-34.64)	(-9.56)	(-4.22)	(-36.39)
$ZIND$	-0.000480***	-0.0000219	0.000348	-0.000334**	-0.000125	-0.000595	-0.00154	-0.000133	-0.000433	0.00344	0.00242	-0.0000460
	(-2.95)	(-0.03)	(0.32)	(-2.11)	(-0.50)	(-0.60)	(-1.55)	(-0.56)	(-0.78)	(1.59)	(0.78)	(-0.09)
$SDROA$	0.0243***	0.0233***	0.0285***	0.0245***	-0.0187***	-0.00782**	-0.00580	-0.0162***	0.0207***	0.00405	0.00613	0.0188***
	(16.87)	(6.23)	(5.72)	(18.78)	(-12.55)	(-1.97)	(-1.09)	(-11.45)	(6.30)	(0.52)	(0.51)	(6.42)
$BKSIZE$	0.0251***	0.0208***	-0.0104	0.0206***	-0.0217***	-0.00511	-0.00303	-0.0171***	0.0266***	-0.0136	0.0208	0.0246***
	(12.81)	(2.83)	(-1.60)	(11.98)	(-7.91)	(-0.88)	(-0.73)	(-7.95)	(3.96)	(-1.11)	(1.50)	(4.51)
$BKHHI$	0.0128***	-0.0157	0.0712***	0.0151***	-0.00471	0.00397	0.118***	-0.000573	0.0312***	0.0513	0.0857	0.0381***
	(3.45)	(-0.61)	(2.69)	(4.15)	(-1.00)	(0.21)	(2.84)	(-0.12)	(2.61)	(1.05)	(0.95)	(3.29)
$BKMSML$	-0.0252***	-0.0172	-0.0495	-0.0253***	0.00422*	-0.000481	-0.000959	0.00717***	-0.0565***	0.0256	-0.00781	-0.0542***
	(-12.23)	(-1.31)	(-1.17)	(-12.53)	(1.76)	(-0.04)	(-0.04)	(3.09)	(-8.94)	(0.84)	(-0.08)	(-9.01)
$BKPOP$	0.00455***	0.00687	0.0152**	0.00522***	-0.000279	0.00388	0.00303	-0.000266	0.00328	-0.000472	0.0324	0.00371
	(5.60)	(1.50)	(2.16)	(6.63)	(-0.25)	(1.24)	(0.49)	(-0.25)	(1.30)	(-0.06)	(1.24)	(1.56)
$BKPDNS$	0.00457***	0.0186*	-0.0150	0.00544***	-0.00122	0.00758	0.0146	-0.000180	0.00506	0.0139	-0.0447	0.00662
	(2.76)	(1.74)	(-1.17)	(3.33)	(-0.54)	(0.83)	(1.07)	(-0.08)	(0.84)	(0.78)	(-0.98)	(1.15)
$BKICHG$	-0.0937***	-0.218***	-0.153**	-0.110***	-0.0467***	-0.142***	-0.235***	-0.0578***	-0.110***	-0.719***	-0.663***	-0.142***
	(-15.36)	(-6.44)	(-1.99)	(-18.41)	(-6.22)	(-3.70)	(-4.36)	(-7.86)	(-5.80)	(-8.12)	(-3.16)	(-7.67)
$MBHC$	0.00550***	-0.0142**	-0.00806	0.00402**	-0.0115***	-0.00391	-0.0804***	-0.0139***	-0.000857	-0.0344**	-0.0316	-0.00342
	(2.83)	(-2.37)	(-0.97)	(2.11)	(-3.33)	(-0.61)	(-3.04)	(-4.15)	(-0.11)	(-1.99)	(-1.11)	(-0.47)
$OBHC$	0.00390**	-0.0137***	-0.00368	0.00343**	-0.00696**	-0.000497	-0.0794***	-0.00928***	-0.00874	-0.0391**	-0.0352	-0.01000

Continued on next page

Table 5.8 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(2.35)	(-2.80)	(-0.75)	(2.16)	(-2.23)	(-0.08)	(-3.04)	(-2.98)	(-1.33)	(-2.40)	(-1.45)	(-1.60)
MRG	0	-0.0235***	0	-0.0124***	0	0.00408	0	0.0212***	0	-0.0255**	0	-0.0295***
	(.)	(-3.09)	(.)	(-7.94)	(.)	(0.79)	(.)	(10.60)	(.)	(-1.98)	(.)	(-6.19)
ACQ	-0.00398***	0.00371	0.00574	-0.00348***	-0.000761	-0.000230	0.00666	-0.000498	-0.000482	0.00245	0.0219	0.000103
	(-3.99)	(0.88)	(1.29)	(-3.62)	(-0.62)	(-0.04)	(1.20)	(-0.42)	(-0.15)	(0.16)	(1.04)	(0.03)
Constant	-0.373***	-0.428***	-0.0175	-0.334***	0.566***	0.191**	0.192*	0.506***	0.570***	1.099***	0.221	0.584***
	(-15.48)	(-4.04)	(-0.19)	(-15.52)	(16.60)	(2.33)	(1.96)	(17.86)	(7.21)	(5.95)	(0.56)	(8.70)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.270	0.504	0.425	0.284	0.166	0.0856	0.343	0.156	0.263	0.396	0.301	0.269
N	19793	1059	529	21381	19793	1059	529	21381	19793	1059	529	21381

These results suggest that management deliberately reduced risk as a reaction to the crisis. Thus results show that pre-crisis MA increases both tier 1 ratio ($T1R$) and the ratio of liquid assets over total assets ($LAGTA$) and decreases nonperforming loans as a reaction to the crisis (NPL). This holds in particular for small banks but, albeit not always significantly also for medium banks and the full sample. It does not hold for large banks, where, for $T1R$, coefficients are the opposite sign but insignificant. A possible explanation for this difference is the likely greater interconnectedness of large financial institutions. Here, rapid de-risking is much more difficult due to the greater volumes, greater time-lags and, most importantly, greater danger of contagion. This aligns well with the insignificantly positive coefficient on managerial ability in large banks for liquidity creation. Together, this may be tentative evidence that very large banks may have been "too big to manage" even for able managers. In contrast to their more successful colleagues at small and medium banks, large bank managers may have been overconfident in normal times. This could potentially have induced risk-taking that subsequently proved hard to control under the shock of the crisis.

Furthermore, the coefficient on the crisis dummy, δ_c, also exhibits plausible signs. Thus one would expect that when funding is scarce, liquidity reserves will be depleted as a reaction to the onset of the financial crisis. In addition, one would also expect that, in an environment where asset values drop precipitously, losses accumulate and equity is hard to raise, tier 1 capital will decline. Furthermore, the coefficient on δ_c in Panel A is also as expected. Even though bad news on loans may have been kept hidden by managers during good times, a strong exogenous shock will likely have induced its revelation, resulting in increased loan provisions as indicated by a significantly positive δ_c (see also Balboa, López-Espinosa and Rubia, 2013). Hence the majority of the evidence supports the interpretation that managerial ability facilitated banks' reactions to the financial crisis in terms of risk reduction and therefore provides support for A4.

In sum, the analyses show at least tentatively that, first, that banks that were more ably managed before the crisis reduce their liquidity creation activity more strongly than other banks, which supports hypothesis A3b. Second, the findings indicate more emphatically that more ably managed banks find it easier to react to the crisis by increasing their capitalization and liquidity holdings. This supports the view expressed in hypothesis A4 that more able managers are better able to react to exogenous shocks by de-risking. Together these findings strongly suggest that the resilience of banks to exogenous shocks depends, at least in part, on the ability of their managers.

5.5. Robustness Checks

In order to ensure that the main findings are robust, this section discusses results from a number of tests. Many of these are reported in greater detail in Appendix C. First, as the main findings rely on winsorized data, I want to ascertain that this manipulation is not driving results. Therefore unreported analyses replicate the regressions without winsorizing, with qualitatively unchanged results.

Second, Berger and Bouwman (2009) argue that to combat endogeneity, one strategy is to use 3-year *lagged* moving average values of the independent variables. The main analysis has used 3-year moving averages. Hence I replicate Berger and Bouwman's (2009) strategy and find robust results (see the appendix, Section C.2.7).

Third, the main source of endogeneity in the data is likely the presence of bank size, risk weighted assets, volatility of ROA and the Z-Score as regressors because components of these can enter into the calculation of liquidity creation, as well as being involved in managerial decision making. Arguably, it is much more difficult to suggest endogeneity between the remaining variables such as bank holding company status or bank-market characteristics and liquidity creation. The main reasons are twofold. First, these characteristics are drawn from outside the balance sheet and thus do not enter into the calculation of liquidity creation in any way. Second, characteristics like bank holding company status or population growth in the bank's markets are much more difficult, if not impossible, for management to influence and very slow to react. One can, for instance, envision that management might be tempted to leave low growth markets and relocate operations to more dynamic ones. However, such a project suffers from time-lags of various sorts. Thus the problem must be identified, a decision taken, alternative facilities bought or leased and existing operations divested. In contrast, liquidity creation can be influenced much more rapidly by, for example, simply varying capitalization or the asset mix on the balance sheet. Hence it is very unlikely that there will be endogeneity between the slow-moving remaining variables and rapidly changing liquidity creation. Therefore Section C.2.2 reruns the analyses omitting $BKSIZE$, $CREDRSK$, $SDROA$ and $ZIND$. The results are robust to this modification. Moreover they indicate that if any endogeneity is driving results, the effects are biasing results against the outcomes asserted in this investigation. This becomes apparent from the fact that previously insignificant coefficients on managerial ability during the crisis become significantly negative when these potentially endogenous regressors are removed from the analysis.

Fourth, it is important to investigate the sensitivity of the results to the choice of liquidity creation measure. Therefore Section C.1.3 replicates the main analysis using both Berger and Bouwman's (2009) $CATNONFAT$ measure as well as the liquidity transformation gap of Deep and Schaefer (2004). While it has been noted that this latter variable is somewhat more crude than that of Berger and Bouwman (2009), it does provide a useful check on the robustness of the main results. Using these measures of liquidity creation I find that the results for the whole sample period as well as the results for the financial crisis hold in qualitative terms.

Fifth, the base case analysis uses the entire period (1996-2010) to identify the influence that managerial ability has on liquidity creation and the other bank characteristics in normal times. As this period includes the financial crisis itself, results could be driven by these effects. Therefore Section C.2.4 reruns the base case regressions for the 1996-2006 subsample. Results are not sensitive to the sample period. In addition, Section C.2.5 also investigates whether restricting the crisis to 2008-2009 or 2007-2008 instead of 2007-2009 influences the results. In this case results reveal that it is primarily the period 2007-2008 that is responsible for the reduction in liquidity creation by more able managers. This is consistent with one's expectation given Bebchuk and Goldstein's (2011) hypothesis: under this hypothesis a shock makes the liquidity creation of all other banks more uncertain and thus makes a reduction in liquidity creation individually more desirable for any given bank. This effect is primarily driven by uncertainty. This uncertainty is likely to have been greatest in 2007-2008 when regulators and central banks were only beginning to react to the shock of the financial crisis and the full extent of the balance sheet contamination experienced by the various banks may not have been well understood. This is likely to have changed in 2008-2009 with the introduction of more robust measures for the support of the financial system. Furthermore, Section C.2.1 analyzes the results that obtain for a placebo crisis between 2003 and 2004. The observed effects are either opposite to the main analysis (liquidity creation) or far too small to account for the full effects observed in the main analysis. Hence the analysis is also robust to this modification.

Finally, one main source of concern with the validity of the results is the use of a regression error term as proxy for managerial ability. While Demerjian, Lev and McVay (2012) demonstrate the validity of this approach, there are many possible parametrizations of the MA measure that each have their specific strengths and weaknesses. Thus efficiency scores can be obtained from various methods such as data envelopment analysis (DEA), stochastic frontier analysis and, more recently, generalized frontier analysis (GFA). While DEA makes the assumption that the data is observed without noise, SFA requires the assumption of a known functional form for the revenue function as well as the distributions of error terms. GFA on the other hand requires neither of these assumptions. In addition, Demerjian, Lev and McVay's (2012) work postulates revenue maximization as the goal of management whereas this analysis assumes that profit maximization is the main objective. Hence Appendix C.1 considers the different outcomes of the analysis if MA is parametrized using revenue efficiency obtained variously from SFA, DEA and GFA. Furthermore, for each of these efficiency scores, the first stage Tobit regressions that eventually yield MA as the residual can plausibly be conducted with various sets of regressors. The appendix investigates whether this choice has any effect on the results. Specifically, it investigates whether including the bank holding company type as a regressor along with the original control variables changes results. This approach is chosen because this characteristic is both likely to influence bank performance (bank holding company members typically have access to the BHC's resources in crisis times) and likely to be beyond the individual manager's immediate control. In addition, one could argue that out of the original regressors that are inspired by Demerjian, Lev and McVay (2012) and Cantrell (2013), $BKSIZE$, $NUMEMP$ and $LEVRAG$ have the potential to be endogenous to bank efficiency. Therefore the appendix introduces a third set of regressors that excludes these potentially endogenous variables while instead including the bank demographic controls as defined in the main analysis. Finally, the Tobit regressions can be conducted over yearly subsamples of banks, as in the main analysis, or for a pooled sample of bank data separately. The former approach, chosen in the main analysis, has the advantage that any potential confounding look-ahead effects that emanate from including future data in the regression can be avoided. The appendix also checks whether the pooled sample approach, advocated by Demerjian, Lev and McVay (2012), affects results. In sum, Appendix C.1 replicates the analysis for 24 different specifications of managerial ability and finds very robust results.

5.6. Conclusion

This chapter investigates the importance of managerial ability for the performance of banks. In particular, it analyzes the influence of managerial ability on liquidity creation and risk-taking. While liquidity creation is a primary and crucial function of banking organizations, their risk-taking behavior is also important to regulators and the general public. Common wisdom suggests that more able managers should be creating more liquidity with their institution in normal times. In addition, this chapter hypothesizes that more ably managed banks also take more risk. The results provide support for both hypotheses.

The analysis then proceeds to ask what the impact of the shock represented by the financial crisis of 2007-09 may have been regarding liquidity creation and risk-taking and what role managerial ability has to play in this context. The impact of the crisis, as mediated by managerial ability, on liquidity creation is an empirical question since the theoretical literature suggests that banks should decrease their liquidity creation, while some empirical findings contest this assertion. This chapter investigates this question using a difference-in-differences approach and finds tentative evidence that the former case holds true: more ably managed banks reduce liquidity creation during the financial crisis than their less well managed peers.

Finally, the investigation analyzes the significance of managerial ability for bank risk during the crisis using the same identification strategy. The hypothesis is that more able managers are better at de-risking their bank during the crisis. Consistent with this hypothesis, the findings show that more ably managed banks do in fact reduce their bank's risk during the crisis. All of the results are found to be robust to a large number of checks.

These findings imply that regulators may do well in favoring better managed banks in normal times in order to maximize the creation of liquidity in the economy. In crisis times, on the other hand, more ably managed banks may require additional incentives to lend.

6. Limitations and Directions for Further Research

In the broadest sense, this thesis stands in the tradition of empirical research in Finance. As such, it is subject to a number of general limitations that are common to the field. As I will argue in the following, I have attempted to forestall as many of these limitations as possible by way of copious robustness checks. However, given the limited scope of any thesis, room for improvement of the proposed methods and findings remains. This section briefly discusses these issues. In addition, some suggestions for future research emanate specifically from the limitations to the present work. This chapter also sketches some of these points.

General concerns that might be raised with respect to the findings reported in this thesis include problems of the data used, the way it was gathered as well as the computational methods used to obtain the results. Specifically, panel datasets in Finance suffer from survivorship bias. As unsuccessful banks are bought or closed, only the "fittest" survive. Thus financial datasets are inherently biased towards successful institutions. In the present context this may bias results towards more efficient banks. This issue is mitigated by the large sample size used in this work. Specifically, because the frontier specifications used in this thesis rely on a relatively densely populated sample space, the presence or absence of a small number of failed banks is less likely to severely skew results than it would be in a more sparse sample. A further mitigating factor is the fact that the present sample begins during a period where the bulk of the consolidation in the US banking industry, documented for example by Tregenna (2009), had already taken place. However, the possibility that survivorship bias remains can not be conclusively eliminated. A further concern relates to the data gathering and processing procedures. The data was mainly obtained from the Call Reports made available by the Chicago Federal Reserve. This large database of detailed bank balance sheet data requires a substantial amount of collation and organization in order to become empirically exploitable. Therefore ample room for data processing errors exists. However, in so far as this was possible I have tried to mitigate potential issues of this nature by grounding the rules for computing key variables as well as eliminating variables and observations in the literature. In addition, prior studies make it possible for the resultant data to be compared against previous results at least on a cross-sectional basis. Thus, for instance, I have compared the average values of inputs and outputs as well as prices obtained in this thesis against those reported in Berger and Mester (2003) and found very small differences on average. Hence the risk of data manipulation errors has been substantially reduced. Finally, the present work has required the implementation of a variety of algorithms for the computation of efficiency. One reason for this is the fact that standard software packages that are available for this purpose, such as FRONTIER 4.1 (see e.g. Coelli, 1996), have proved unable to handle the size of the present dataset. In addition, the GFA method is entirely new and therefore had to be custom-implemented. Thus the routines required for the calculation of DEA, SFA and GFA efficiency scores were implemented in MATLAB. This, however, creates the possibility that programming errors may be driving some of the results. In order to address this issue, care was taken to thoroughly debug the code by using results and datasets available in the literature (see e.g. Battese and Coelli, 1995, Coelli, Rao, O'Donnell and Battese, 2005). These exercises showed no discrepancies between results computed by way of the hand-coded versus the publicly available algorithms, to the level of accuracy available in the printed sources. This has substantially reduced the concern that computational errors are driving the results presented in this thesis.

In terms of the specific empirical work carried out in this thesis, one could argue that the GFA method itself is of a class of algorithms that are met with skepticism in the financial literature. This is because nonparametric methods are in general not underpinned by theoretical considerations. This thesis has made the effort to mitigate precisely this concern in the first empirical chapter (Chapter 3). There it is shown that GFA efficiency scores exhibit plausible properties relative to other, established efficiency parametrization methods as well as relative to performance indicators, which do not rely on the frontier concept. In addition, this thesis has argued that a method that is data driven is precisely what is required in cases where a theoretical foundation is absent such as, for example, in the case of shareholder value efficiency. One could argue that Chapter 3 should also have considered revenue and profit efficiency. In fact, the corresponding efficiency scores have been computed for all methods and the statistical and validation analyses have also been run. However, from the perspective of validating the GFA algorithm, reporting these results is redundant. This is because, once it has been shown that GFA is able to fit both a lower frontier (for example a cost frontier) and upper frontier (for example a shareholder value frontier) to the data, then revenue and profit efficiency bring no new or more exacting standards to the task since they are both upper frontiers, similar to SHVE. Hence the analyses of revenue and profit efficiency are not tabulated in the interest of brevity. However, it is the case that the GFA algorithm can be improved to facilitate future research. Specifically, at present the algorithm requires a manual setting of the asymmetry parameter. In this thesis, this decision was made using a grid search across various configurations of the parameter space. However, it would be desirable to be able to provide future researchers with, at the very least, a heuristic rule of thumb similar to that proposed for the number of orthogonal series terms in the Flexible Fourier approach (Mitchell and Onvural, 1996). A further refinement along these lines could be the development of an algorithm that automatically selects the ANN parametrization, in particular the asymmetry parameter, based on the given dataset. Furthermore, the GFA method is, in principle, able to predict cost, revenue, profit and shareholder value efficiency simultaneously. Implementing this capability would give it a further advantage over SFA and DEA since both these methods need to be run separately for each efficiency score. This extension also has the potential to improve the quality of predictions due to the richer information set. This, however, would require some non-trivial modifications to the algorithm. Specifically, these modifications would have to allow for the frontier component of the algorithm to take into account both upper frontiers (for example profit frontiers) and lower frontiers (for example cost frontiers) simultaneously. Finally, the SFA method has been extended so as to be able to handle panel data (Battese and Coelli, 1995). A similar development would constitute an important extension of GFA. Although Crone and Kourentzes (2010) show that ANNs of the type used in this thesis can be used for time series data, it is not unlikely that, given the high level of persistence of efficiency scores, better results for sequential data processing may be achieved with recurrent neural networks (see for example Graves, Mohamed and Hinton, 2013). Finally, and this possible extension applies to all chapters, a possible refinement of the present work could be to use methods that take into account exogenous parameters that influence the shape and position of an efficient frontier when estimating SFA efficiency scores (see for example Good, Nadiri, Röller and Sickles, 1993). In the present thesis this approach has been omitted in order to allow for comparability with the GFA method which, as yet, does not allow for the inclusion of exogenous variables into the frontier specification. Hence, if an appropriate panel data approach for GFA can be devised, it would be worthwhile to also incorporate exogenous variables into this frontier estimation method.

Chapter 4 may raise four important questions. First, the definition of the liquidity efficiency score as a proxy for intermediation quality may be scrutinized. While this choice is grounded in the literature[1], the definition of liquidity efficiency as a proxy for intermediation quality may nonetheless appear somewhat ad hoc. To mitigate this concern, this thesis first considers the relation between liquidity efficiency and liquidity creation. Only once a significantly positive relation has been established, does it proceed to the investigation of the empirical questions. Furthermore, Chapter 4 investigates the liquidity transformation gap of Deep and Schaefer (2004), which does not depend on the efficiency methodology, and finds supporting results. Additionally, the chapter parametrizes the liquidity frontier in two ways, using both SFA and GFA. This constitutes another important check of the robustness of the findings. Secondly, Chapter 4 uses Tobit regressions as the main method of inference, where the dependent variable is itself an estimated quantity. Simar and Wilson (2007) argue that this may make inference imprecise and propose a bootstrapping approach that has been implemented for example by Delis and Tsionas (2009). While applying different estimation methods (Tobit, truncated regression, fixed effects) and using a nonfrontier liquidity measure for robustness, goes some way towards mitigating this concern, an important future extension of this work will be to also conduct a similar bootstrapping exercise. Early attempts at implementing such an approach have proved unsuccessful due to computational constraints outside the scope of this thesis. The third issue that comes to mind regarding Chapter 4 is also relevant for Chapter 5. This limitation is, similar to the preceding one, outside the scope of the present work. Specifically, skepticism is warranted with respect to the liquidity creation measures of Berger and Bouwman (2009). The main point here is that, while their heuristic derivation of the asset and liability classes and the corresponding weights seems plausible enough in normal times, this need not hold in times of crises. Thus the authors classify assets and liabilities according to the ease, cost and time which is required to liquidate these. This classification presupposes the liquidity of securities markets. However, the recent financial crisis has shown that these markets can easily "freeze up". In this case, it is unclear how well actual intermediation activity of banks is captured by the liquidity creation measures proposed in Berger and Bouwman (2009). Again, investigating an entirely unrelated measure of liquidity creation for robustness, the liquidity transformation gap of Deep and Schaefer (2004), both in Chapter 4 and 5 contributes towards alleviating this concern. Nonetheless, investigating the robustness of Berger and Bouwman's (2009)

[1] As an example consider Fiordelisi and Molyneux (2010), who, in one of their robustness checks, substitute changes in shareholder value efficiency for shareholder value creation and thus treat SHVE as a proxy for value creation.

measure of liquidity creation to asset market behavior and developing refinements of this measure constitutes an important component of future research in this area. Fourth and finally, Chapter 4 could be extended by an explicit analysis of market measures of risk and opacity such as return volatility, trading properties or split ratings. This has proved outside the ambit of the present work simply because of the available sample of data, which is limited to mostly non-listed commercial banks. Therefore the findings could be made more robust by investigating similar questions for listed bank holding companies using non-balance sheet measures of fragility and opacity.

While Chapter 4 argues for the use of intermediation quality as a dependent variable, Chapter 5 uses absolute liquidity creation. I argue that these choices are appropriate for two reasons. On the one hand, econometric problems regarding naïve relations between the main variable of interest and liquidity creation, which were the primary motivation for the use of intermediation quality in Chapter 4, do not arise in this context. This is due to the way in which the managerial ability proxy is derived (Demerjian, Lev and McVay, 2012). On the other hand, the predictions of the theories tested in Chapter 5 relate directly to the quantity of liquidity created. The fact that bank liquidity creation depends on the asset mix is of subordinate importance in this context because it is not even implicitly required to address "how" the liquidity arises in order to test the hypotheses of Chapter 5. Second, the results presented in Chapter 5 certainly depend on the measure of managerial ability which comprises the heart of this analysis. Again, the construction of the sample precludes the use managerial fixed effects or press visibility as a robustness check. Such checks certainly constitute a fruitful potential avenue for future research. However, in so far as the sample allows, the present thesis has made every effort to alleviate any remaining concerns with the managerial ability proxy by investigating a total of 24 different specifications of this variable and finding robust results.

7. Conclusion

This thesis complements and expands two strands of the literature. First, the present research contributes to the efficiency literature by developing and testing a new efficiency parametrization method, which relaxes the undesirable assumptions of previous methods. Second, it contributes to the banking literature at large and specifically to the strands of the literature studying intermediation, managerial ability and value creation. In so doing, this present work illuminates a number of previously untested questions raised by the theoretical literature and also provides the impetus for the theoretical literature to consider additional factors in its modeling efforts. In this chapter I briefly summarize the main findings that are developed in Chapters 3-5.

A thorough review of the efficiency literature shows that conventional efficiency parametrization methods rely on assumptions that may not be doing justice to the data generating process at hand. However, the discussion of the literature also shows that existing attempts to use a class of promising nonparametric methods, artificial neural networks, for the purpose of efficiency measurement has so far relied on equally untenable assumptions. This motivates the development of a novel efficiency measurement method, generalized frontier analysis, in Chapter 3. This method's generality gives it the potential of being utilized quite flexibly for efficiency analyses in industries other than banking. However, a credible investigation of the capabilities of this new method requires the comparison of the GFA efficiency scores with the efficiency scores obtained from other methods on various types of efficiency. This exercise is the subject of Chapter 3. This chapter together with the corresponding appendix shows, using the examples of cost and shareholder value efficiency, that GFA can parametrize quite general efficient frontiers. In addition, the results in Chapter 3 suggest that the efficiency scores obtained from GFA and SFA are distinct and complementary but informationally similar. Thus GFA is a valuable alternative method to SFA, especially because it can be applied in cases where other traditional methods like DEA are not available. A particular example of such a case is the concept of shareholder value efficiency, advanced by Fiordelisi (2007). In this context Chapter 3 investigates and validates the SHVE concept by comparing the economic and statistical significance of the SFA- and GFA-

SHVE scores when it comes to explaining value creation. In addition, the SHVE scores are compared to managerial ability in terms of their capability to explain value creation. The results show that SHVE is a more important concept than managerial ability when studying the creation of value. Moreover, findings suggest that GFA scores are more informative about the value creation of US banks. Thus, SFA and GFA can be thought of as complementary methods. Chapters 4 and 5 exploit the resulting availability of a new efficiency parametrization method to ensure the robustness of their respective findings. In sum, Chapter 3 contributes to the literature by devising a new method and investigating and validating this method and the SHVE concept using new data and by showing that the informational value of SHVE exceeds that of managerial ability.

In Chapter 4 the thesis shifts its focus to the question of bank intermediation. The theoretical literature allows for the development of a variety of conflicting but testable hypotheses about the impact that bank fragility and bank opacity will have on the intermediation behavior of the bank. This chapter formalizes these hypotheses and proceeds to disentangle them, using balance sheet measures of opacity and fragility. Recent research by Berger and Bouwman (2009) has made available indicators of liquidity creation. These are used to develop measures of intermediation quality by computing SFA and GFA liquidity efficiency scores. This approach overcomes the problem of potentially spurious, naïve regressions. The chapter finds that the operationalization of fragility and opacity enables a clear rejection of two out of the three alternative hypotheses investigated, leading to the acceptance of the theoretical view of Diamond and Rajan (2001). This result documents that banks' intermediation quality benefits from opacity and from fragility. From the viewpoint of policy makers this finding stresses the need for some level of bank secretiveness. Thus, if regulators wish to extract further information from banks for prudential purposes, these results suggest that any such information should not enter the public domain in order to avoid negative externalities with respect to intermediation quality. The findings in this chapter further show that the impact that opacity has on intermediation quality depends on the opacity of the bank. Thus if banks are already very opaque, the beneficial effects of opacity and fragility for intermediation quality diminish substantially. Overall, this chapter extends the empirical banking literature by disentangling a number of as yet untested hypotheses about the interplay of opacity, fragility and intermediation quality. It also points out that theoretical models of intermediation would do well to explicitly account for the effects of opacity.

The final empirical chapter (Chapter 5) combines the available information on bank intermediation and managerial ability in order to investigate whether the ability of managers plays a role for the volume of bank intermediation activity and for the riskiness of banks. Common wisdom leads one to expect a positive influence of managerial ability on liquidity creation in regular times. However, in times of crisis the evidence is mixed. On the one hand, empirical research shows that managers may have value incentives to increase their liquidity market share during crises. Theoretical work, on the other hand, emphasizes the strong incentives for banks to curtail their lending activity in the face of an exogenous shock. Similarly, while one would expect more able, more confident managers to take more risk in normal times, these same managers should be better able to de-risk their banks during crises. This chapter is the first empirical work to investigate these hypotheses. Specifically, the results show that the hypothesis about the positive impact of managerial ability on liquidity creation in normal times is justified. Furthermore, results indicate that more able managers have a penchant for risk-taking during these periods. However, in the face of crises, this greater risk-taking is offset by a stronger de-risking on the part of more able managers. In addition, as postulated by the theoretical literature, more ably managed banks reduce liquidity creation during crises more than other banks. This finding points to a dilemma on the part of the regulator. On the one hand, more able managers clearly de-risk more effectively and thus contribute to the resilience of the banking system. On the other hand, they commensurately and pro-cyclically reduce their liquidity creation activity at a time when a "freezing up" of the interbank and lending markets is least welcome. Regulators could exploit these findings by providing incentives to more ably managed banks during crises in order to ensure that intermediation activity continues.

Taken together, the findings reported in this thesis provide substantial new insights into the functioning of the banking industry as well as new tools for its investigation. This work further points to promising avenues for future research and provides important conclusions of potential value to policy makers.

A. Appendix to Chapter 3

This chapter provides supplementary information to the main analysis in Chapter 3. Specifically, Section A.1 discusses the data used to parametrize the efficiency scores. Subsequently, Section A.2 provides evidence on some of the robustness checks regarding the analysis of shareholder value efficiency. Finally, Section A.3 conducts a statistical and validation analysis for the case of cost efficiency. This demonstrates the capability of GFA to parametrize this type of efficiency measure and allows for a comparison of the resulting efficiency scores against data envelopment analysis (DEA), another established efficiency measurement method.

A.1. Description of the Data

Table A.1 provides a description of the dataset, in particular it reports summary statistics for the variables used to parametrize the efficient frontier for the period under study. Since the sample encompasses the broad population of US banks, values for stock quantities are on average somewhat smaller than those reported in Bauer, Berger, Ferrier and Humphrey (1998), who use a balanced sample. Data is obtained from the December Call Reports at the Federal Reserve Bank of Chicago. Currency values are in 2005 US dollars. To ensure consistency of the data I compare the summary statistics against the results in Berger (2003) for the year 1997 (not reported) and find discrepancies of less than 5% on average. When considering input quantities, x_1 signifies labor, x_2 denotes financial capital and x_3 stands for core deposits. On the output side, y_1 implies consumer loans, y_2 denotes business loans, y_3 stands for real estate loans and y_4 indicates securities. Off-balance-sheet items as fixed output are represented by z_1. Accordingly, w_1 signifies the price of labor, w_2 denotes the price of financial capital and w_3 stands for the price of core deposits.

Table A.1.: Summary Statistics, Averages Across Banks and Sample Years.

This table reports summary statistics for the main variables used to compute efficiency scores. Specifically, x_1 = labor, x_2 = financial capital, x_3 = core deposits y_1 = consumer loans, y_2 = business loans, y_3 = real estate loans, y_4 = securities, z_1 = off-balance-sheet items (fixed), w_1 = price of labor, w_2 = price of financial capital and w_3 = price of core deposits. EVA stands for economic value added. Values for input and output quantities, equity, fixed assets, cost and EVA are in millions of 2005 US dollars, where adjustment to this basis period was achieved using the GDP implied deflator. Labor (x_1) is measured in the number of full-time equivalent employees. All data are obtained from the December Call Reports available from the US Federal Reserve (Chicago Branch).

Variable	**Mean**	**Standard Deviation**	**MIN**	**MAX**
x_1	197.55	2,732.24	2	213,967.00
x_2	354.78	9,387.34	0.07	969,472.10
x_3	492.22	6,567.28	0.61	636,319.30
y_1	60.55	1,005.37	0	84,001.81
y_2	184.92	4,040.78	0	401,295.80
y_3	266.61	3,641.24	0	370,750.80
y_4	337.55	7,926.45	0.48	998,783.20
z_1	101.59	2,797.38	0	379,477.90
w_1	53.16	11.99	5.22	286.31
w_2	0.07	0.02	0.007	0.49
w_3	0.04	0.01	0.003	0.26
Equity	76.67	1,319.38	0.53	117,810.60
Fixed Assets	10.23	120.53	0	7,997.87
Cost	33.18	616.59	0.17	62,396.95
EVA	7.16	196.10	-19,675.90	22,382.43
$\frac{EVA_t}{Capital\ Invested_{t-1}}$	0.05	0.09	-3.18	7.67

A.2. Robustness Checks - Shareholder Value Efficiency

First, Section A.2.1 investigates whether the SHVE scores obtained from SFA and GFA are able to predict future nonfrontier performance by computing the correlations between efficiency scores in period t and nonfrontier performance indicators in period $t+1$. Second, the results in Bauer, Berger, Ferrier and Humphrey (1998) are obtained for a balanced sample. Therefore Section A.2.2 reruns the complete analysis for a balanced sample of banks. This includes the predictability analysis. In addition, I extend the analysis by investigating the correlation between efficiency scores averaged across time and nonfrontier performance indicators likewise averaged across time, a technique employed by Bauer, Berger, Ferrier and Humphrey (1998) to reduce noise in the estimates. Finally, Section A.2.3 provides additional regression results including lags of the independent variables as well as separate estimates for the subsamples split by size and for an alternative specification of managerial ability. Moreover this section replicates the main analysis using lagged instead of contemporaneous SHVE measures.

A.2.1. Full Sample - Predictability Analysis

This section provides results on the ability of shareholder value efficiency scores to predict nonfrontier performance of banks. Results are reported in Table A.2. The findings show that, as in the main analysis, the efficiency parametrization methods agree in sign where they provide significant correlations. Furthermore, again similar to the main analysis, the signs conform to one's expectation and the GFA efficiency scores are more frequently significant, which suggests that these are more informative than comparable SFA scores. This holds for small and medium banks in particular.

Table A.2.: Correlation of Bank Shareholder Value Efficiency with Leading Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the full population as well as split by size into the smallest 50%, the medium 40% and the largest 10% of banks. The correlation is between efficiency in period t and nonfrontier indicators in period $t+1$. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A:		*Panel B:*		*Panel C:*		*Panel D:*	
		All Banks		*Small Banks*		*Medium Banks*		*Large Banks*	
				0-50%		*50-90%*		*90-100%*	
Correlates		**SFA**	**GFA**	**SFA**	**GFA**	**SFA**	**GFA**	**SFA**	**GFA**
ROA	$+$	0.2356***	0.0717*	0.2318***	0.2506***	0.3072***	0.2385**	0.2241**	0.1902*
$\frac{Total\ Cost}{Total\ Assets}$	$-$	0.0098	-0.0792*	-0.0787*	-0.0741**	-0.0063	-0.0976	0.0029	-0.0465
$\frac{Total\ Revenue}{Total\ Assets}$	$+$	0.1299*	0.0460*	0.0358	0.0803	0.0453	0.0585***	0.0491	0.0564
$\frac{Equity}{Total\ Assets}$	$\pm$	-0.0969*	0.0097*	0.0185	-0.1699**	-0.0202	-0.1458*	-0.0521	-0.1294
$\frac{EVA}{Total\ Assets}$	$+$	0.3604*	0.0643**	0.2996**	0.4401***	0.5200***	0.4267***	0.3800***	0.3862*
$\frac{EP}{Total\ Assets}$	$+$	0.3886***	0.1289**	0.3702***	0.4294***	0.5764***	0.4016***	0.3982***	0.3091***
$\frac{Cap.\ Charge}{Total\ Assets}$	$-$	-0.2502*	-0.6375***	-0.1351***	-0.3190***	-0.1002	-0.1022**	-0.0322*	-0.2718
$\frac{Liquid\ Assets}{Total\ Assets}$	$\pm$	-0.0374**	0.0367**	0.0241	0.0016*	0.0108	-0.0668	-0.0219	-0.0976
$\frac{Nonp.\ Loans}{Total\ Loans}$	$-$	-0.0294*	-0.0498**	-0.0435	-0.0670	-0.0569	-0.1056	-0.0216	-0.0554

A.2.2. Balanced Sample

This section reports results obtained from a balanced sample of banks. Results indicate that the main analysis is robust to sample selection.

A.2.2.1. Statistical Analysis

Table A.3 reports results regarding the statistical analysis.

Here I find that GFA and SFA provide quite similar distributions of efficiency scores (Panel A). The measures of central tendency are now somewhat higher for SFA than for GFA. Moreover, the correlations between the different efficiency scores increase substantially (Panel B). Furthermore, the overlaps between top and bottom performers (Panel C) remain large, significant and remarkably balanced between top and bottom banks. Hence I conclude that the statistical analysis is qualitatively unaffected by transitioning from a full to a balanced sample.

Table A.3.:
Statistical Analysis of Shareholder Value Efficiency Parametrization Methods, Balanced Sample. This table reports results relating to the statistical analysis. Panel A shows distributional properties computed on a yearly basis and then averaged across years. Panel B reports correlations between the two efficiency measures. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Panel C reports the overlap between top and bottom percentiles of banks as classified by the two efficiency parametrization methods. * indicates significant difference from 25% (10%, 5%, 1%) at the 10% level (Chi-square test, two-tailed). SFA indicates stochastic frontier analysis, GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$).

Panel A: Distributional Properties

	SFA	**GFA**
mean	0.7792	0.6836
median	0.8027	0.7058
min	0.0317	-0.6851
max	0.9868	1.0000
std	0.1231	0.0973
skewness	-2.0211	-4.1556

Panel B: Correlations

Pearson	0.5239***
Spearman	0.5587***
Kendall	0.4274***

Panel C: Overlaps

Top 25%	**Bottom 25%**
0.5586*	0.5912*
Top 10%	**Bottom 10%**
0.4282*	0.4858*
Top 5%	**Bottom 5%**
0.3644*	0.3987*
Top 1%	**Bottom 1%**
0.3082*	0.3096*

A.2.2.2. Validation Analysis

This section discusses the results obtained from the validation analysis run on a balanced sample of banks. Specifically, Table A.4 reports the main findings.

Panel A reports results based on rank correlations between contemporaneous efficiency scores and nonfrontier performance measures for the balanced sample of banks. As in the main analysis, I find that, whenever significant, GFA and SFA efficiency scores seem to agree on the relation with nonfrontier performance indicators. Again, and this result likewise permeates the analyses in Panels B and C, the GFA scores are more frequently significantly different from zero, which further strengthens the conclusion that these scores are more informative than those obtained from SFA. Panel B repeats the analysis with nonfrontier performance measures shifted one period into the future, while Panel C considers the relation between the time-series average of efficiency scores and nonfrontier performance measures. Both cases deliver results that are qualitatively unchanged vis-à-vis the main analysis.

Table A.4.:
Correlation of Bank Shareholder Value Efficiency with Nonfrontier Performance Measures, Balanced Sample.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the population of banks. Panel A shows results for contemporaneous nonfrontier indicators. In Panel B the correlation is between efficiency in period t and nonfrontier indicators in period $t+1$. Panel C reports the correlation between the time series average of efficiency scores and the corresponding average of nonfrontier indicators. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A: Contemporaneous		*Panel B: Leading*		*Panel C: Average*	
Correlates	E[sgn]	**SFA**	**GFA**	**SFA**	**GFA**	**SFA**	**GFA**
ROA	+	0.2042***	0.2013*	0.1771	0.1515*	0.2387***	0.1647***
$\frac{Total\ Cost}{Total\ Assets}$	−	0.0131	-0.0740**	0.0089	-0.0609*	0.0115	-0.1007***
$\frac{Total\ Revenue}{Total\ Assets}$	+	0.0595	0.0995**	0.0668*	0.1070***	0.0838***	0.1212***
$\frac{Equity}{Total\ Assets}$	±	-0.0783**	-0.0980	-0.0722**	-0.1001*	-0.0713***	-0.0540**
$\frac{EVA}{Total\ Assets}$	+	0.4424**	0.3881**	0.3171*	0.2384*	0.4114***	0.1751***
$\frac{EP}{Total\ Assets}$	+	0.4639**	0.3707***	0.3681*	0.2551**	0.4819***	0.2387***
$\frac{CapitalCharge}{Total\ Assets}$	−	-0.3481***	-0.5110***	-0.3076*	-0.5029***	-0.5818***	-0.7719***
$\frac{Liquid\ Assets}{Total\ Assets}$	±	0.0245	-0.0198**	0.0089	-0.0286	0.0674***	0.0524**
$\frac{Nonperf.\ Loans}{Total\ Loans}$	−	-0.0645	-0.0764	-0.0433	-0.0536	-0.0331	-0.0536**

A.2.3. Further Regression Results

This section provides a number of additional regression scenarios for shareholder value efficiency. Specifically, the analyses consider the results obtained if the regressions are run separately for subsamples of the bank population (Section A.2.3.1), the case in which lags of the independent variables are included in the regressions (Section A.2.3.2) and results obtained with a different specification of managerial ability (Section A.2.3.3).

A.2.3.1. Regressions for Subsamples

The following discussion considers the results obtained for regressions of value creation on shareholder value efficiency separately for subsamples of the bank population. First, Tables A.5-A.7 investigate the regression results and the economic significance of the coefficients. Subsequently, Table A.8 considers the contribution of the SFA and GFA efficiency scores to the explanation of the value creation of US banks.

In terms of the general regression results and the economic significance of the efficiency scores, I find strong support for the main findings. Thus, Specifications 1, 3 and 5 show that the coefficients on the GFA scores are much greater than those on SFA. Furthermore, the substantial reduction of the t-statistic for SFA-SHVE when GFA-SHVE is included in the regression (Specification 5) holds for small and medium banks in particular. And even for large banks (Table A.7), while the SFA-SHVE coefficient is greater than GFA-SHVE, the t-statistic of GFA increases while that of SFA-SHVE decreases when both are included as regressors. These findings are supported by results in Specifications 2, 4 and 6, which include control variables. This confirms the conclusion drawn in the main analysis, namely that the economic significance and information content of GFA-SHVE with respect to value creation is greater that of the SFA shareholder value efficiency scores. Similarly, robust findings hold for Specifications 7-10. Specifically, these show that the economic significance of the GFA-SHVE scores is greater, especially for small and medium banks, when control variables are included. Results also document that medium and large bank findings confirm the signs observed for cost and revenue efficiency in the main analysis. Finally, considering the impact of managerial ability in Specifications 11 and 12, results are also robust, especially for small and medium banks. Here, managerial ability is highly significantly and positively associated with value creation but the economic relevance of this measure is small, as in the main analysis. Furthermore, GFA-SHVE scores are economically more important than those from SFA. This changes in the case of large banks. In addition, for large banks, managerial ability becomes insignificant. Overall, across Specifications 2, 4, 6,

Table A.5.: Regression Analysis of Shareholder Value Efficiency, Small Banks (0-50% of the Size Distribution).

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi - \text{eff}$) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA}$	0.0298***	0.0154***			0.0134***	0.0108***	0.0303***	0.0154***			0.0108***	0.0146***
	(43.12)	(26.13)			(28.55)	(22.07)	(45.77)	(30.05)			(22.05)	(30.78)
$\psi - \text{eff}_{GFA}$			0.0497***	0.0317***	0.0458***	0.0297***			0.0497***	0.0318***	0.0296***	0.0452***
			(71.72)	(38.11)	(69.74)	(37.93)			(70.83)	(37.78)	(37.91)	(67.31)
$x - \text{eff}_{SFA}$							0.00726***	0.00104				
							(3.99)	(0.65)				
$\tau - \text{eff}_{SFA}$							0.00386***	0.00155***				
							(6.42)	(4.11)				
$x - \text{eff}_{GFA}$									0.00202***	-0.000813**		
									(4.94)	(-2.23)		
$\tau - \text{eff}_{SFA}$									0.00389***	0.00191***		
									(12.35)	(7.12)		
MA											0.00215***	0.00247***
											(7.24)	(7.55)
ROA		0.0453***		0.0298***		0.0280***		0.0452***		0.0298***	0.0280***	
		(51.02)		(32.03)		(29.76)		(50.91)		(31.97)	(29.71)	
NPL		0.00121***		0.00168***		0.00132***		0.00112***		0.00162***	0.00130***	-0.00351***
		(3.15)		(5.18)		(4.17)		(2.89)		(4.99)	(4.10)	(-11.20)
$BKSIZE$		0.0122***		0.0195***		0.0204***		0.0119***		0.0192***	0.0206***	0.0291***
		(10.55)		(18.24)		(19.04)		(10.11)		(17.21)	(19.13)	(26.17)
$LEVRAG$		0.0251***		0.0169***		0.0171***		0.0251***		0.0171***	0.0168***	0.00787***
		(33.12)		(25.98)		(26.36)		(32.08)		(26.08)	(25.69)	(12.72)
Constant	0.112***	0.0895***	0.0588***	0.0358***	0.0910***	0.0840***	0.111***	0.0892***	0.133***	0.118***	0.0842***	0.0914***
	(102.80)	(96.48)	(73.89)	(34.41)	(116.51)	(106.48)	(99.80)	(97.12)	(133.32)	(136.61)	(105.70)	(118.60)
Adj. R^2	0.579	0.772	0.740	0.811	0.752	0.818	0.584	0.772	0.742	0.811	0.819	0.779
N	52834	52834	52834	52834	52834	52834	52834	52834	52834	52834	52834	52834

Table A.6.: Regression Analysis of Shareholder Value Efficiency, Medium Banks (50-90% of the Size Distribution).

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi - \text{eff}$) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA}$	0.0463***	0.0247***			0.0256***	0.0178***	0.0462***	0.0246***			0.0177***	0.0259***
	(40.53)	(21.91)			(30.26)	(20.18)	(40.37)	(21.87)			(20.16)	(30.24)
$\psi - \text{eff}_{GFA}$			0.0433***	0.0256***	0.0357***	0.0222***			0.0433***	0.0256***	0.0223***	0.0334***
			(49.89)	(23.58)	(46.05)	(23.11)			(49.86)	(23.45)	(23.29)	(42.51)
$x - \text{eff}_{SFA}$							-0.00221	-0.00276**				
							(-1.47)	(-1.99)				
$\tau - \text{eff}_{SFA}$							0.00195***	0.000836				
							(2.91)	(1.47)				
$x - \text{eff}_{SFA}$									-0.000638	-0.00156*		
									(-0.65)	(-1.78)		
$\tau - \text{eff}_{SFA}$									-0.00203***	-0.000454		
									(-3.35)	(-0.75)		
MA											0.00184**	0.00267***
											(2.25)	(3.27)
ROA		0.0428***		0.0355***		0.0314***		0.0427***		0.0355***	0.0313***	
		(34.11)		(26.25)		(22.97)		(33.99)		(26.28)	(22.84)	
NPL		-0.00358***		-0.00169		-0.00257**		-0.00357***		-0.00163	-0.00258**	-0.0111***
		(-3.10)		(-1.49)		(-2.33)		(-3.10)		(-1.44)	(-2.33)	(-11.99)
$BKSIZE$		0.00881***		0.00863***		0.0103***		0.00900***		0.00904***	0.0104***	0.0138***
		(7.24)		(7.20)		(8.55)		(7.41)		(7.48)	(8.61)	(11.00)
$LEVRAG$		0.0228***		0.0207***		0.0195***		0.0229***		0.0206***	0.0194***	0.0108***
		(22.09)		(21.16)		(19.92)		(22.02)		(20.51)	(20.22)	(11.55)
Constant	0.165***	0.133***	0.0548***	0.0464***	0.132***	0.121***	0.0184***	0.0273***	0.113***	0.118***	0.121***	0.134***
	(78.52)	(64.05)	(45.58)	(33.87)	(75.49)	(69.27)	(10.49)	(15.26)	(70.49)	(83.33)	(69.18)	(76.82)
Adj. R^2	0.476	0.627	0.562	0.648	0.592	0.662	0.477	0.627	0.562	0.648	0.662	0.614
N	42991	42991	42991	42991	42991	42991	42991	42991	42991	42991	42991	42991

Table A.7.: Regression Analysis of Shareholder Value Efficiency, Large Banks (90-100% of the Size Distribution).

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi-$eff) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x-$ eff and $\tau-$ eff indicate cost and revenue efficiency. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA}$	0.0371***	0.0217***			0.0317***	0.0201***	0.0370***	0.0217***			0.0201***	0.0301***
	(12.45)	(5.76)			(9.94)	(5.39)	(12.35)	(5.72)			(5.38)	(9.38)
$\psi-\text{eff}_{GFA}$			0.0284***	0.0149***	0.0233***	0.0132***			0.0295***	0.0156***	0.0132***	0.0221***
			(4.87)	(4.18)	(5.11)	(4.57)			(4.80)	(4.19)	(4.55)	(5.06)
$x-\text{eff}_{SFA}$							-0.00363	-0.00268				
							(-1.57)	(-1.31)				
$\tau-\text{eff}_{SFA}$							-0.00113	-0.00215				
							(-0.42)	(-0.87)				
$x-\text{eff}_{GFA}$									-0.0138***	-0.00848***		
									(-5.75)	(-4.64)		
$\tau-\text{eff}_{GFA}$									-0.00359	-0.000783		
									(-1.08)	(-0.25)		
MA											-0.00112	-0.000740
											(-0.54)	(-0.32)
ROA		0.0487***		0.0497***		0.0439***		0.0488***		0.0492***	0.0439***	
		(9.58)		(10.22)		(8.07)		(9.60)		(10.25)	(8.08)	
NPL		-0.00259		-0.00302		-0.00329		-0.00243		-0.00283	-0.00320	-0.0199***
		(-0.66)		(-0.75)		(-0.82)		(-0.62)		(-0.70)	(-0.81)	(-5.16)
$BKSIZE$		0.0265***		0.0259***		0.0267***		0.0268***		0.0225**	0.0264***	0.0214**
		(3.03)		(2.97)		(3.10)		(3.06)		(2.51)	(3.07)	(2.45)
$LEVRAG$		0.0242***		0.0243***		0.0226***		0.0243***		0.0235***	0.0226***	0.0134***
		(9.17)		(9.80)		(8.63)		(9.23)		(9.50)	(8.72)	(5.59)
Constant	-0.0275***	-0.000128	-0.00134	0.0341***	-0.0197***	0.00279	-0.0240***	0.00181	-0.0651***	0.0320***	0.00250	-0.0140**
	(-5.34)	(-0.02)	(-0.25)	(6.60)	(-3.64)	(0.40)	(-3.72)	(0.22)	(-8.92)	(5.83)	(0.35)	(-2.13)
Adj. R^2	0.312	0.381	0.306	0.377	0.335	0.388	0.312	0.381	0.310	0.378	0.388	0.347
N	10739	10739	10739	10739	10739	10739	10739	10739	10739	10739	10739	10739

8, 10, 11 and 12, coefficients on the control variables are robust. Thus, as in the main analysis, I find that profitability (ROA), size ($BKSIZE$) and leverage ($LEVRAG$) all contribute to value creation. While the main analysis finds a negative influence of nonperforming loans (NPL), this finding is not confirmed for small banks, but does hold for medium and large banks.

Next, in Table A.8, I consider the contribution of the SHVE scores to the explanation of value creation in US banks across subsamples of the bank population. The main analysis found that GFA-SHVE scores contribute substantially more to the explanation of value creation than comparable SFA scores, in particular when control variables were excluded. When considering the same analysis split by subsamples of the bank population, I find results to be robust. In fact, while for large banks (Panel C) SFA and GFA perform roughly on par, the advantage of GFA for small and medium banks (the majority of observations in the sample) is even more pronounced than in the main analysis when considering the subsamples separately (Panels A and B). This holds even in the presence of managerial ability, whose explanatory contribution is low across all subsamples. This strongly confirms the findings of the main analysis.

Table A.8.:
Contribution of Efficiency Measures to Adjusted R^2 in % of Adjusted R^2 for Subsamples of the Bank Population Split by Size.

This table reports the contribution to adjusted R^2 made by each variable in the regressions in Tables A.5-A.7 in Panels A-C respectively. Specifically, each cell indicates how much the regressor contributes to the explanatory power of the regression indicated by the column heading. The contribution to adjusted R^2 was computed as $C_j = \frac{R^2 - R_j^2}{R^2}$, where C_j is the contribution of the j$^{\text{th}}$ variable, R_j^2 is the adjusted R^2 computed without that variable and R^2 is the total adjusted R^2. $\psi-$eff represents shareholder value efficiency, while $x-$eff and $\tau-$eff indicate cost and revenue efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012).

Panel A: Small Banks (0-50%)												
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA}$	11.3	2.0			1.6	0.9	11.3	2.0			0.9	1.8
$\psi-\text{eff}_{GFA}$			30.7	6.8	23.0	5.7			30.3	6.8	5.7	20.7
$x-\text{eff}_{SFA}$							0.6	0.0				
$\tau-\text{eff}_{SFA}$							0.2	0.0				
$x-\text{eff}_{GFA}$									0.0	0.0		
$\tau-\text{eff}_{GFA}$									0.2	0.0		
MA											0.1	0.1
Panel B: Medium Banks (50-90%)												
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA}$	24.9	4.4			5.1	2.0	24.6	4.4			2.0	5.0
$\psi-\text{eff}_{GFA}$			36.3	7.6	19.5	5.2			36.3	7.6	5.3	15.5
$x-\text{eff}_{SFA}$							0.0	0.1				
$\tau-\text{eff}_{SFA}$							0.0	0.0				
$x-\text{eff}_{GFA}$									0.0	0.0		
$\tau-\text{eff}_{GFA}$									0.0	0.0		
MA											0.0	0.1
Panel C: Large Banks (90-100%)												
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA}$	13.3	3.3			8.7	2.8	13.2	3.3			2.8	7.5
$\psi-\text{eff}_{GFA}$			11.4	2.3	6.8	1.7			12.0	2.4	1.7	5.8
$x-\text{eff}_{SFA}$							0.1	0.0				
$\tau-\text{eff}_{SFA}$							0.0	0.0				
$x-\text{eff}_{GFA}$									1.4	0.4		
$\tau-\text{eff}_{GFA}$									0.1	0.0		
MA											0.0	0.0

A.2.3.2. Regressions Including Lags of the Efficiency Scores

This section reruns the main analysis but includes lags of the various efficiency scores to account for the fact that processes such as changes in efficiency may take time in order to affect the bank's outcome. This exercise not only provides robustness to the results from the main analysis, but specifically investigates the low explanatory contribution obtained from the cost and revenue efficiency scores. Concretely, if efficiency enhancing strategies take time to implement, the low explanatory power of contemporaneous cost and revenue efficiency might be mitigated by including lags of these variables.

Table A.9 reports the results relating to the economic significance of shareholder value efficiency. Results suggest that the main conclusions hold. Specifically, the economic significance of the GFA SHVE scores in Specification 3 is greater than that of SFA SHVE in Specification 1 and likewise, when both SFA and GFA scores are included in Specification 5. In Specification 2, vs. 4 and in Specification 6, SFA has a slight edge however. A similar picture presents itself when cost and revenue efficiency are included in Specifications 7-10. Finally, this main result holds in the presence of managerial ability in Specifications 11 and 12. Importantly, I find that managerial ability is still significantly positive but not economically significant for the explanation of SHVE.

Table A.9.: Regression Analysis of Shareholder Value Efficiency Including Lagged Independent Variables.

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi-$eff) as well as a set of control variables and their lags. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x-$eff and $\tau-$eff indicate cost and revenue efficiency. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi-\text{eff}_{SFA,t}$	0.0304***	0.0189***			0.0231***	0.0176***	0.0301***	0.0181***			0.0175***	0.0242***
	(48.56)	(38.58)			(31.13)	(37.14)	(48.90)	(38.76)			(37.18)	(32.48)
$\psi-\text{eff}_{SFA,t-1}$	0.00616***	0.00263***			0.00289***	0.00213***	0.00689***	0.00346***			0.00220***	0.00367***
	(15.00)	(7.72)			(6.56)	(6.20)	(16.31)	(9.77)			(6.38)	(8.80)
$\psi-\text{eff}_{SFA,t-2}$	0.00493***	0.00178***			0.00304***	0.00198***	0.00503***	0.00234***			0.00191***	0.00363***
	(13.11)	(5.72)			(8.00)	(5.98)	(13.39)	(7.71)			(5.72)	(9.90)
$\psi-\text{eff}_{SFA,t-3}$	0.00241***	0.000731**			0.00243***	0.00150***	0.00255***	0.00111***			0.00138***	0.00274***
	(6.23)	(2.28)			(6.00)	(4.39)	(6.19)	(3.35)			(4.02)	(6.92)
$\psi-\text{eff}_{GFA,t}$			0.0335***	0.0161***	0.0291***	0.0146***			0.0348***	0.0170***	0.0147***	0.0274***
			(15.23)	(12.04)	(14.80)	(12.68)			(14.34)	(11.16)	(12.90)	(14.56)
$\psi-\text{eff}_{GFA,t-1}$			0.00575***	0.00163**	0.00365***	0.000402			0.00602***	0.00217***	0.000374	0.00254***
			(4.85)	(2.51)	(3.68)	(0.75)			(4.70)	(3.02)	(0.71)	(2.76)
$\psi-\text{eff}_{GFA,t-2}$			0.00206***	-0.000192	0.000852	-0.000824**			0.00194***	-0.0000304	-0.000814**	0.000158
			(3.60)	(-0.50)	(1.56)	(-2.06)			(3.01)	(-0.07)	(-2.04)	(0.31)
$\psi-\text{eff}_{GFA,t-3}$			0.000473	-0.000791**	0.000165	-0.000947**			0.000374	-0.000571	-0.000888**	-0.000384
			(1.06)	(-2.10)	(0.36)	(-2.49)			(0.80)	(-1.47)	(-2.33)	(-0.88)
$x-\text{eff}_{SFA,t}$							-0.00311***	-0.00459***				
							(-3.92)	(-6.51)				
$x-\text{eff}_{SFA,t-1}$							0.00349***	0.00239***				
							(7.51)	(5.99)				
$x-\text{eff}_{SFA,t-2}$							0.000236	0.00117**				
							(0.42)	(2.53)				
$x-\text{eff}_{SFA,t-3}$							0.00346***	0.00355***				
							(4.18)	(4.79)				
$\tau-\text{eff}_{SFA,t}$							0.000234	-0.00119**				
							(0.41)	(-2.46)				
$\tau-\text{eff}_{SFA,t-1}$							0.000881**	-0.00127***				
							(2.18)	(-3.98)				
$\tau-\text{eff}_{SFA,t-2}$							0.0000782	-0.000532*				
							(0.22)	(-1.93)				
$\tau-\text{eff}_{SFA,t-3}$							0.000851**	0.000915***				
							(2.45)	(3.27)				
$x-\text{eff}_{GFA,t}$									-0.00827***	-0.00570***		
									(-10.18)	(-10.47)		
$x-\text{eff}_{GFA,t-1}$									-0.000362	-0.00258***		
									(-0.98)	(-8.49)		
$x-\text{eff}_{GFA,t-2}$									0.000917*	-0.000768*		
									(1.75)	(-1.95)		
$x-\text{eff}_{GFA,t-3}$									0.00329***	0.00165***		
									(7.12)	(4.76)		
$\tau-\text{eff}_{GFA,t}$									-0.000221	0.00111***		
									(-0.60)	(3.54)		
$\tau-\text{eff}_{GFA,t-1}$									0.00219***	0.00180***		
									(5.60)	(5.67)		

Continued on next page

Table A.9 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\tau-\mathrm{eff}_{GFA,t-2}$									-0.000255	-0.00107***		
									(-0.59)	(-3.04)		
$\tau-\mathrm{eff}_{GFA,t-3}$									-0.000162	0.000189		
									(-0.44)	(0.58)		
MA											0.00258***	0.00303***
											(7.23)	(7.03)
ROA		0.0472***		0.0439***		0.0391***		0.0473***		0.0436***	0.0391***	
		(51.58)		(34.25)		(33.78)		(51.57)		(32.28)	(33.87)	
NPL		0.00123**		0.00158***		0.00119**		0.00124**		0.00143**	0.00118**	-0.00898***
		(2.05)		(2.66)		(2.05)		(2.03)		(2.41)	(2.03)	(-12.77)
$BKSIZE$		0.0322***		0.0172***		0.0302***		0.0340***		0.0186***	0.0309***	0.0352***
		(12.08)		(6.32)		(11.43)		(12.78)		(6.63)	(11.58)	(11.99)
$LEVRAG$		0.0252***		0.0238***		0.0224***		0.0251***		0.0242***	0.0222***	0.0109***
		(32.16)		(29.57)		(28.88)		(32.27)		(29.87)	(28.29)	(13.92)
Constant	0.134***	0.0484***	0.0502***	0.0652***	0.0334***	0.0464***	0.0286***	0.0487***	0.0481***	0.0646***	0.0461***	0.0286***
	(139.84)	(34.12)	(54.29)	(57.33)	(28.54)	(34.70)	(19.94)	(31.33)	(35.56)	(42.05)	(34.09)	(18.16)
Adj. R^2	0.537	0.709	0.584	0.703	0.631	0.728	0.539	0.713	0.590	0.707	0.728	0.651
N	72191	72191	72191	72191	72191	72191	72191	72191	72191	72191	72191	72191

Table A.10.:
Contribution of Efficiency Measures to Adjusted R^2 in % of Adjusted R^2 for Regressions Including Lagged Independent Variables.

This table reports the contribution to adjusted R^2 made by each group of variables in the regressions in Table A.9. Specifically, each cell indicates how much the group of regressors contribute to the explanatory power of the regression indicated by the column heading. The contribution to adjusted R^2 was computed as $C_j = \frac{R^2 - R_j^2}{R^2}$, where C_j is the contribution of the j[th] group of regressors, R_j^2 is the adjusted R^2 computed without that group of regressors and R^2 is the total adjusted R^2. $\psi - \text{eff}$ represents shareholder value efficiency, while $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012).

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA}$	35	-0.8			7.5	3.4	16.1	3.7			3.4	7.6
$\psi - \text{eff}_{GFA}$			40.3	-1.7	15	2.5			24.3	3.5	2.6	12.3
$x - \text{eff}_{SFA}$							0.4	0.4				
$\tau - \text{eff}_{SFA}$							0.0	0.0				
$x - \text{eff}_{GFA}$									0.9	0.5		
$\tau - \text{eff}_{GFA}$									0.1	0.1		
MA											0.1	0.1

When considering the statistical value of the two efficiency scores in explaining value creation in Table A.10 I find that the GFA SHVE scores continue to have an advantage over SFA. That is the case when the other control variables are not included in the analysis. Interestingly, in Specifications 2 and 4, the contribution to the adjusted R^2 made by both methods becomes negative, probably due to the proliferation of coefficients with a strongly similar information content. As has been noted from the viewpoint of economic significance, cost and revenue efficiency continue to be negligible when it comes to explaining value creation in US banks. The same is true for managerial ability. Overall, this analysis again confirms the main findings.

A.2.3.3. Regressions Using an Alternative Parametrization of Managerial Ability

Finally, one might suspect that the particular parametrization of managerial ability that is used in the main analysis drives results in some critical fashion. In order to investigate this question, Table A.11 replicates the regressions which include MA but uses a different specification of this variable. Specifically, it uses stochastic frontier analysis for the parametrization of managerial ability instead of using data envelopment analysis. These results show that the decision to follow Demerjian, Lev and McVay's (2012) original specification in parametrizing managerial ability is not driving results. Specifically,

	(1)	(2)
$\psi - \text{eff}_{SFA}$	0.0160***	0.0220***
	(26.07)	(31.04)
$\psi - \text{eff}_{GFA}$	0.0175***	0.0313***
	(15.45)	(19.48)
MA	0.000418	0.00209***
	(1.30)	(5.89)
ROA	0.0376***	
	(33.33)	
NPL	-0.00122*	-0.0109***
	(-1.72)	(-15.77)
$BKSIZE$	0.0237***	0.0280***
	(8.17)	(9.23)
$LEVRAG$	0.0225***	0.0129***
	(31.94)	(19.22)
Constant	0.0517***	-0.0138***
	(34.93)	(-8.75)
Bank Effects	yes	yes
Year Effects	yes	yes
Adj. R^2	0.604	0.539
N	106564	106564

Table A.11.:
Regression Analysis of Shareholder Value Efficiency, Alternative MA Parametrization
This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi - \text{eff}$) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are z-transformed.

the managerial ability measure is insignificantly positive when ROA is also included among the controls and significantly positive but economically small when ROA is excluded. Moreover, the SHVE measure parametrized by GFA is still economically more meaningful than its SFA-based counterpart. In addition, Table A.12 shows that the contribution of MA to value creation is nearly unchanged vis-à-vis the main analysis.

Table A.12.:
Contribution of Efficiency Measures to Adjusted R^2 in % of Adjusted R^2, Alternative MA Parametrization.
This table reports the contribution to adjusted R^2 made by each variable in the regressions in Table A.11. Specifically, each cell indicates how much the regressor contributes to the explanatory power of the regression indicated by the column heading. The contribution to adjusted R^2 was computed as $C_j = \frac{R^2 - R_j^2}{R^2}$, where C_j is the contribution of the j[th] variable, R_j^2 is the adjusted R^2 computed without that variable and R^2 is the total adjusted R^2. $\psi - \text{eff}$ represents shareholder value efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012) and using SFA to parametrize revenue efficiency.

	(1)	(2)
$\psi - \text{eff}_{SFA}$	2.9	6.4
$\psi - \text{eff}_{GFA}$	3.4	15.5
MA	0.0	0.1

A.2.3.4. Regressions Using Lagged Shareholder Value Efficiency

This section replicates the main analysis using lags of SHVE instead of contemporaneous values to mitigate possible endogeneity concerns. Table A.13 reports the main results. These indicate that the qualitative findings of the main analysis are unchanged. More specifically, especially when excluding other controls, the GFA efficiency scores are economically more significant for the creation of value in banks. Cost and revenue efficiency are of only marginal importance on the other hand. Moreover managerial ability, when included is both economically and statistically insignificant when ROA is also among the regressors and of only marginal importance when excluding ROA.

These results are generally confirmed when considering the contribution to adjusted R^2 made by the various efficiency scores in Table A.14. Specifically, the statistical significance of the GFA efficiency scores is strictly greater than that of SFA when controls are excluded from the regressions and comparable otherwise. Moreover, cost and revenue efficiency as well as managerial ability contain almost no information on the creation of value in banks, which is similar to the main analysis.

Overall these additional findings confirm the main results.

Table A.13.: Regression Analysis of Shareholder Value Efficiency using lagged SHVE.

This table reports results from regressions of EVA scaled by lagged total assets on shareholder value efficiency ($\psi -$ eff) as well as a set of control variables. These include return on assets (ROA), leverage ($LEVRAG$), the ratio of nonperforming loans to total loans (NPL) and bank size ($BKSIZE$). $x -$ eff and $\tau -$ eff indicate cost and revenue efficiency respectively. MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012). SFA stands for stochastic frontier analysis, GFA stands for generalized frontier analysis. All regressions include year and bank fixed effects. T-statistics are reported in parentheses and stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Standard errors are clustered by bank; all regressors are Z-transformed.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA,t-1}$	0.0119***	0.00487***			0.00901***	0.00435***	0.0119***	0.00500***			0.00437***	0.00865***
	(28.70)	(15.47)			(21.48)	(14.03)	(28.73)	(15.87)			(14.09)	(21.97)
$\psi - \text{eff}_{GFA,t-1}$			0.0137***	0.00325***	0.0116***	0.00232***			0.0136***	0.00328***	0.00232***	0.00974***
			(19.67)	(8.87)	(17.93)	(6.54)			(19.62)	(8.96)	(6.54)	(16.38)
$x - \text{eff}_{SFA}$							-0.00598***	-0.00615***				
							(-9.37)	(-11.34)				
$\tau - \text{eff}_{SFA}$							0.00130***	-0.000561*				
							(3.10)	(-1.66)				
$x - \text{eff}_{GFA}$									0.00136***	-0.00165***		
									(3.09)	(-5.09)		
$\tau - \text{eff}_{GFA}$									-0.0000415	0.00177***		
									(-0.12)	(6.35)		
MA											-0.000252	0.00156***
											(-0.80)	(4.20)
ROA		0.0518***		0.0519***		0.0514***		0.0519***		0.0519***	0.0514***	
		(61.34)		(60.80)		(60.03)		(61.26)		(60.86)	(59.97)	
NPL		0.000425		0.000452		0.000448		0.000424		0.000395	0.000461	-0.0163***
		(0.54)		(0.58)		(0.58)		(0.55)		(0.51)	(0.59)	(-22.58)
$BKSIZE$		0.0117***		0.00927***		0.0112***		0.0108***		0.00969***	0.0113***	0.0133***
		(4.80)		(3.81)		(4.61)		(4.39)		(4.03)	(4.61)	(4.89)
$LEVRAG$		0.0286***		0.0286***		0.0284***		0.0287***		0.0289***	0.0284***	0.0159***
		(43.34)		(42.60)		(42.46)		(43.47)		(42.27)	(42.36)	(20.15)
Constant	0.0410***	0.0688***	0.0546***	0.0723***	0.0483***	0.0701***	0.0372***	0.0654***	0.0450***	0.0170***	0.0701***	0.0579***
	(36.49)	(54.45)	(51.58)	(54.25)	(43.31)	(57.27)	(31.18)	(51.45)	(38.78)	(14.10)	(56.85)	(39.63)
Adj. R^2	0.424	0.653	0.429	0.652	0.436	0.653	0.427	0.656	0.429	0.652	0.653	0.473
N	100186	100186	100186	100186	100186	100186	100186	100186	100186	100186	100186	100186

Table A.14.:
Contribution of Efficiency Measures to Adjusted R^2 in % of Adjusted R^2.

This table reports the contribution to adjusted R^2 made by each variable in the regressions in Table A.13. Specifically, each cell indicates how much the regressor contributes to the explanatory power of the regression indicated by the column heading. The contribution to adjusted R^2 was computed as $C_j = \frac{R^2 - R_j^2}{R^2}$, where C_j is the contribution of the j$^{\text{th}}$ variable, R_j^2 is the adjusted R^2 computed without that variable and R^2 is the total adjusted R^2. $\psi - \text{eff}$ represents shareholder value efficiency, while $x - \text{eff}$ and $\tau - \text{eff}$ indicate cost and revenue efficiency. SFA indicates stochastic frontier analysis. GFA indicates generalized frontier analysis (asymmetry parameter $a = 1000$). MA stands for managerial ability and has been computed following Demerjian, Lev and McVay (2012).

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\psi - \text{eff}_{SFA}$	17.7	14.2			1.6	0.2	17.7	14.2			0.2	1.3
$\psi - \text{eff}_{GFA}$			18.7	14.0	2.8	0.1			18.6	14.0	0.1	1.8
$x - \text{eff}_{SFA}$							0.7	0.5				
$\tau - \text{eff}_{SFA}$							0.0	0.0				
$x - \text{eff}_{GFA}$									0.0	0.0		
$\tau - \text{eff}_{GFA}$									0.0	0.0		
MA											0.0	0.0

A.3. Analysis of Cost Efficiency

Generalized frontier analysis has been formulated so as to be able to accommodate various types of efficiency. To illustrate this capability, this section conducts the analysis previously performed for SHVE also in the case of cost efficiency. The analysis of cost efficiency allows a direct comparison of GFA not only with SFA but also with DEA as well as with the previous results of Bauer, Berger, Ferrier and Humphrey (1998). This investigation serves to further deepen the understanding of the performance of the GFA method vis-à-vis the other, established methods.

A.3.1. Statistical Analysis

The first step is to investigate the statistical properties of the cost efficiency scores provided by the various methods. Table A.15 reports the results of the analysis for the full sample of banks.

These results show a striking similarity between the cost efficiency scores provided by SFA and GFA (Panel A). This holds both for the order of magnitude in terms of the measures of central tendency as well as minimum, maximum, dispersion and skewness. The results further document that the distributional properties of the DEA efficiency scores are substantially different from the other methods except for minima and maxima.

Most importantly, DEA cost efficiency scores are positively skewed. This is unexpected in a mature and highly technological industry like banking. The correlations between the various methods (Panel B), confirm findings in the prior literature (specifically in Bauer, Berger, Ferrier and Humphrey (1998) and Huang and Wang (2002)). Thus correlations between the full distribution of efficiency scores are low between SFA and DEA and, in the case of the linear Pearson correlation between GFA and DEA, even negative. On the other hand, the correlations between SFA and GFA are positive, sizeable and highly significant. This confirms that these two methods produce efficiency scores that are quite comparable. Panel C analyzes the overlaps between subsamples of banks classified as either highly efficient or very inefficient by any two methods and finds additional confirmatory results. Thus the scores obtained from SFA and DEA and those from DEA and GFA are in moderate agreement at best, a result confirmed by Bauer, Berger, Ferrier and Humphrey (1998). SFA and GFA, on the other hand, classify very similar banks as highly efficient. The agreement between these two methods in terms of classification of inefficient banks is somewhat lower, but still significantly greater than chance.

The next step is to examine the distributional properties of the efficiency scores obtained for a balanced sample of banks. The distributional properties in Panel A of Table A.16 show that the main findings are generally supported. Thus the SFA and GFA methods still produce very similar results. Interestingly, the DEA scores are now much more compatible with the scores obtained from the other two methods. Given this strong change in the DEA scores and the small change in the GFA or SFA scores, one can also conclude that the much greater correlations between DEA and GFA as well as the greater overlaps that now obtain in Panels B and C are due to the change in the DEA scores to align better with the GFA scores. This confirms prior findings which show that DEA is very sensitive to the composition of the sample in terms of the efficiency scores that it delivers. Fortunately, this shortcoming is not observed in either SFA or GFA. This further strengthens the conclusion that GFA is a plausible efficiency parametrization method. The strong association between SFA and GFA in terms of overlaps and correlation remains, in particular for very efficient banks.

Overall, these findings are both comparable with prior literature and also rule out the possibility that the GFA efficiency scores are simply an artifact. However, in order to form a more complete picture, the validation analysis, reported in Section A.3.2, will be necessary.

Table A.15.: Statistical Analysis of Cost Efficiency.

This table reports results relating to the statistical analysis. Panel A shows distributional properties computed on a yearly basis and then averaged across years. Panel B reports correlations between the efficiency measures. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Panel C reports the overlap between top and bottom percentiles of banks as classified by the efficiency parametrization methods. * indicates significant difference from 25% (10%, 5%, 1%) at the 10% level (Chi-quare test, two-tailed). SFA indicates stochastic frontier analysis, DEA indicates data envelopment analysis and GFA indicates generalized frontier analysis (asymmetry parameter $b = 1000$).

	Panel A: Distributional Properties		
	SFA	**DEA**	**GFA**
mean	0.9264	0.6321	0.9101
median	0.9337	0.6255	0.9238
min	0.1617	0.1561	0.1604
max	0.9889	1.000	1.000
std	0.0443	0.1153	0.0528
skewness	-4.5383	0.4154	-5.6337
	Panel B: Correlations		
	Pearson	**Spearman**	**Kendall**
(SFA - DEA)	0.1680***	0.1938***	0.1325***
(SFA - GFA)	0.1597***	0.4665***	0.3633***
(DEA - GFA)	-0.0402**	0.0082*	0.0052*
	Panel C: Overlaps		
	Top 25%	**Bottom 25%**	
(SFA - DEA)	0.3291*	0.3500*	
(SFA - GFA)	0.6798*	0.3254*	
(DEA - GFA)	0.2963*	0.2208*	
	Top 10%	**Bottom 10%**	
(SFA - DEA)	0.1662*	0.2099*	
(SFA - GFA)	0.6285*	0.1082*	
(DEA - GFA)	0.1570*	0.0811*	
	Top 5%	**Bottom 5%**	
(SFA - DEA)	0.1067*	0.1640*	
(SFA - GFA)	0.5450*	0.0817*	
(DEA - GFA)	0.1145*	0.0488*	
	Top 1%	**Bottom 1%**	
(SFA - DEA)	0.0782*	0.1989*	
(SFA - GFA)	0.1865*	0.0901*	
(DEA - GFA)	0.0605*	0.0435*	

Table A.16.: Statistical Analysis of Cost Efficiency, Balanced Sample.

This table reports results relating to the statistical analysis. Panel A shows distributional properties computed on a yearly basis and then averaged across years. Panel B reports correlations between the efficiency measures. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. Panel C reports the overlap between top and bottom percentiles of banks as classified by the efficiency parametrization methods. * indicates significant difference from 25% (10%, 5%, 1%) at the 10% level (Chi-square test, two-tailed). SFA indicates stochastic frontier analysis, DEA indicates data envelopment analysis and GFA indicates generalized frontier analysis (asymmetry parameter $b = 1000$).

	Panel A: Distributional Properties		
	SFA	**DEA**	**GFA**
mean	0.9582	0.7686	0.9013
median	0.9635	0.7616	0.9131
min	0.4650	0.3207	0.4244
max	0.9931	1.000	0.9996
std	0.0291	0.1049	0.0516
skewness	-5.7458	0.1566	-1.9893
	Panel B: Correlations		
	Pearson	**Spearman**	**Kendall**
(SFA - DEA)	0.2310***	0.2507***	0.1727***
(SFA - GFA)	0.1938***	0.4032***	0.3176***
(DEA - GFA)	0.0851	0.1335**	0.0907**
	Panel C: Overlaps		
	Top 25%	**Bottom 25%**	
(SFA - DEA)	0.3576*	0.3945*	
(SFA - GFA)	0.6621*	0.2844*	
(DEA - GFA)	0.3547*	0.2789*	
	Top 10%	**Bottom 10%**	
(SFA - DEA)	0.1575*	0.2731*	
(SFA - GFA)	0.6186*	0.1030*	
(DEA - GFA)	0.1956*	0.1235*	
	Top 5%	**Bottom 5%**	
(SFA - DEA)	0.0987*	0.2296*	
(SFA - GFA)	0.5917*	0.0756*	
(DEA - GFA)	0.1212*	0.0842*	
	Top 1%	**Bottom 1%**	
(SFA - DEA)	0.0786*	0.2236*	
(SFA - GFA)	0.3032*	0.0800*	
(DEA - GFA)	0.1334*	0.0893*	

A.3.2. Validation Analysis

This section discusses the results of the validation analysis regarding cost efficiency. First, I turn to results obtained from the full sample of banks and for subsamples split by bank size. As in the case of SHVE, following Feng and Serletis (2009), the analysis splits the sample into strata holding the 50% smallest, the medium 40% and the largest 10% of banks, and efficiency is estimated separately for each stratum. This re-estimation of efficiency for each subsample implements the hypothesis that instead of a shared production function there might be meaningful differences in the technologies used by small, medium and large banks. Correlations are reported between cost efficiency scores on the one hand and nonfrontier performance indicators on the other.

If a bank engages in aggressive cost reduction efforts in order to become more cost efficient, the motive will usually be profit maximization. Hence it is natural to expect a positive association with return on assets (ROA). Correspondingly, one would expect that the component of EVA that relates to the cost of capital will be lower for more cost efficient banks, assuming that they extend their cost saving efforts to capital budgeting decisions. Hence a negative association between cost efficiency and $\frac{Cap.\ Charge}{Total\ Assets}$ is expected. Similarly, provided cost saving initiatives are successful, economic profits should be positively associated with cost efficiency. This leads to the expectation of a positive correlation between cost efficiency and $\frac{EP}{Total\ Assets}$. Note, however, that, because of the univariate nature of the analysis, this does not necessarily imply that more cost efficient banks need be more value creating because observing the expected signs on economic profits and capital charge does not guarantee that banks are both efficient managers of capital and strong generators of economic profits. However, both would be necessary for value creation. In addition, less tangible adverse effects of cost saving initiatives can include demotivation of staff as well as less thorough management of market risk etc. (Fiordelisi and Molyneux, 2010). Hence the association between cost efficiency and value creation ($\frac{EVA}{Total\ Assets}$) is difficult to anticipate. The focus on risk management also influences the amount of liquid assets held. While these assets are costly in an opportunity cost sense, they ensure low bank risk, which may decrease funding cost. Hence the expectation is equally ambiguous for $\frac{Liquid\ Assets}{Total\ Assets}$. Intuitively, more cost efficient banks should also have lower overall cost so that one would expect correlations between cost efficiency and $\frac{Total\ Cost}{Total\ Assets}$ to be negative. However, the influence on revenue is not so clear. Thus cost reduction initiatives may well lead to a decrease in the overall volume of operations that is more than offset by a decrease in revenue, for example because of branch closures that may lead to loss of market share.

However, a leaner organizational structure, induced by greater cost efficiency, may well lead to a greater revenue generation relative to the asset base of the bank. Hence the coefficient on $\frac{Total\ Revenue}{Total\ Assets}$ is difficult to pin down ex ante. The same holds for equity over total assets. Whether a more cost efficient structure entails a reduction of risk and thus a reduction of borrowing costs or a tighter financing structure with the aim of achieving lower dollar cost of capital is difficult to predict. The "Efficiency Risk Hypothesis" posits that a more efficient bank, in the expectation of higher future returns, will maintain a lower capital base (Berger and Bonaccorsi di Patti, 2006). However, part of the related "Efficient Structure Hypothesis" predicts that more efficient banks will persistently generate higher profits, which may be driving higher equity ratios (e.g. Berger, 1995, Mester, 1996 and Casu and Girardone, 2006). Both are plausible yet conflicting predictions as to the association between cost efficiency and $\frac{Equity}{Total\ Assets}$. Hence it is difficult to form a prior about this variable. Finally, the cost to banks from nonperforming loans can be substantial. Anticipating this, I expect that banks will steer their cost efficiency initiatives in such a way as to ensure a high quality loan portfolio. This is equivalent to the "Efficiency Lending Quality Hypothesis" of Chortareas, Girardone and Ventouri (2011). Therefore the expectation is to observe a negative sign on $\frac{Nonp.\ Loans}{Total\ Loans}$.

The main findings bear out many of these conjectures. Concretely, I find that banks that are highly ranked on cost efficiency also tend to be highly ranked in terms of return on assets (ROA). This is an intuitive result and holds both for all banks and across all subsamples. However, only GFA is consistently able to provide a significant correlation. Similarly straightforward is the finding that more cost efficient banks have lower levels of cost ($\frac{Total\ Cost}{Total\ Assets}$), which is robust across methods and subsamples as well. GFA and DEA are in agreement in terms of the association between cost efficiency and revenue as a fraction of assets as well, while SFA is uninformative in this respect ($\frac{Total\ Revenue}{Total\ Assets}$). Specifically, the coefficient indicates that more cost efficient banks will also be more revenue generating, which suggests that the "lean organization" interpretation, sketched above, appears more likely. While SFA and GFA suggest that, across all banks, holding more equity is positively associated with cost efficiency, thus emphasizing the risk motive, DEA suggests the opposite, i.e. stresses the cost of capital motive ($\frac{Equity}{Total\ Assets}$). All methods agree, at least for the full sample of banks, that more cost efficiency is on average detrimental for value creation ($\frac{EVA}{Total\ Assets}$). On the other hand, GFA suggests that for small and medium sized banks the opposite may be the case. SFA and DEA are uninformative in this regard. All methods are in agreement that this observation is due to a lower economic profit ($\frac{EP}{Total\ Assets}$) that is partially offset by an equally lower (in the case of DEA higher) capital charge ($\frac{Cap.\ Charge}{Total\ Assets}$). Consistent with expectations, small and medium banks hold lower levels of liquid assets to the extent that they are more cost efficient ($\frac{Liquid\ Assets}{Total\ Assets}$). This is confirmed by GFA and DEA, while SFA is uninformative. However, in the full sample case, SFA and GFA indicate the opposite. It is not surprising that subsamples may create different rankings than the full sample, especially given that the cost efficiency estimates were computed for the different samples separately. Nonetheless, the higher holdings of liquid assets in the full sample indicated by these methods are puzzling. It may be the case that the risk aversion motive is more pervasive for the full sample of banks. In any event, the coefficients for small and medium banks are plausible in light of the revenue coefficients observed before. Lower levels of liquid assets should translate to greater revenue. Finally, all methods seem to agree that more cost efficient banks are also better loan monitors, as expected ($\frac{Nonp.\ Loans}{Total\ Loans}$). I observe some important changes in sign between the full sample of banks and the subsamples. This provides support for the conjecture that banks of different sizes are subject to somewhat different production functions as noted for example in the economies of scale literature (see e.g. McAllister and McManus, 1993, Wheelock and Wilson, 2001, Berger, Miller, Petersen, Rajan and Stein, 2005, and Asaftei, 2008). Overall, GFA aligns well with both SFA and DEA, while more frequently providing significant information about bank performance as in the shareholder value efficiency case.

As before, in the case of shareholder value efficiency, I rerun my analysis of rank correlations between efficiency scores and nonfrontier performance indicators as a predictability analysis. This analysis considers the correlation between cost efficiency in period t and the nonfrontier performance measures in period $t+1$. Numerous observations made in the previous analysis hold in the predictability analysis as well. Thus, for example, more cost efficient banks are likely to have higher profitability as well as lower levels of cost in the future (ROA, $\frac{Total\ Cost}{Total\ Assets}$), a finding borne out by all methods. Furthermore, as in the main analysis, present cost efficiency is likely to be associated with higher future revenue generation ($\frac{Total\ Revenue}{Total\ Assets}$). While full sample results indicate that present cost efficiency tends to correlate with greater future levels of equity ($\frac{Equity}{Total\ Assets}$) in the full sample, GFA suggests that the opposite is the case for small banks. This result again mirrors the principal analysis. As before, GFA suggests that contemporaneous cost efficiency is positively associated with future value creation for small and medium banks, while all methods conclude that the opposite holds in the main sample ($\frac{EVA}{Total\ Assets}$). This is confirmed by compatible results for economic profits ($\frac{EP}{Total\ Assets}$). Finally, findings regarding $\frac{Cap.\ Charge}{Total\ Assets}$, $\frac{Nonp.\ Loans}{Total\ Loans}$ and $\frac{Liquid\ Assets}{Total\ Assets}$ are again similar to the main analysis. This investigation shows that the cost efficiency

Table A.17.: Correlation of Bank Cost Efficiency with Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the full population as well as split by size into the smallest 50%, the medium 40% and the largest 10% of banks. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. DEA indicates data envelopment analysis. GFA indicates generalized frontier analysis (asymmetry parameter $b = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A: All Banks			*Panel B: Small Banks 0-50%*			*Panel C: Medium Banks 50-90%*			*Panel D: Large Banks 90-100%*		
Correlates		**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**
ROA	+	0.0085	0.1750***	0.0806**	0.1479**	0.2115***	0.2402***	0.1516	0.1413***	0.3354***	0.0891	0.0648	0.1835**
$\frac{Total\ Cost}{Total\ Assets}$	−	-0.2410***	-0.6621***	-0.2515***	-0.5287***	-0.5635***	-0.1545*	-0.6712***	-0.5550***	-0.3800*	-0.5655***	-0.5431***	-0.4706***
$\frac{Total\ Revenue}{Total\ Assets}$	±	-0.0292	0.1482**	0.0224*	-0.0061	0.1171**	0.2299**	0.0057	0.1082*	0.1606*	0.0034	0.0393	-0.0004
$\frac{Equity}{Total\ Assets}$	±	0.1483***	-0.0401***	0.2554***	0.0074	0.0228	-0.195***	-0.0131	-0.0898	0.0169	0.0286	-0.1289	0.1164
$\frac{EVA}{Total\ Assets}$	±	-0.1953*	-0.0458***	-0.2273***	-0.0085	-0.0110	0.1938*	-0.0283	-0.0042	0.1045*	-0.0076	-0.0618	-0.0194
$\frac{EP}{Total\ Assets}$	+	-0.0905***	-0.1102***	-0.0611*	-0.0512	-0.0289	0.0952**	-0.0722*	-0.0426	0.0876*	-0.0238	-0.0835	0.0250
$\frac{Cap.\ Charge}{Total\ Assets}$	−	-0.3741***	0.1290***	-0.7918***	-0.0506*	-0.0819***	0.3001***	-0.0566**	-0.0234	0.2444	-0.1127**	0.1339**	-0.2561***
$\frac{Liquid\ Assets}{Total\ Assets}$	±	0.0896***	-0.1139*	0.2072***	-0.0030	-0.0523**	-0.3151***	-0.0229	-0.1343**	-0.1793***	-0.0361	-0.0984	-0.0628
$\frac{Nonp.\ Loans}{Total\ Loans}$	−	-0.0330	-0.0992**	-0.0049**	-0.1125***	-0.0982***	0.0022	-0.1061*	-0.0883*	0.0132	-0.0615	-0.0490	-0.0529

scores have the ability to meaningfully predict future bank performance. It also confirms that GFA is more frequently significant than either DEA or SFA, which further strengthens the conclusion that the efficiency scores obtained from this method are more informative.

Finally, I consider the validation analysis for cost efficiency across a balanced sample of banks. As in the shareholder value efficiency case, I investigate three different settings reported in Panels A-C of Table A.19. Panel A analyzes the rank correlation between cost efficiency scores and nonfrontier performance measures for a balanced sample of banks. Panel B considers the predictability analysis for the balanced sample and Panel C consider the rank correlation between time-series averages of cost efficiency scores and nonfrontier performance measures.

This analysis confirms across all settings and methods many of the previous findings. Specifically, more cost-efficient banks have lower levels of cost and are more profitable, both contemporaneously and in the future (ROA). While only significant in the average case (Panel C), GFA and DEA also confirm the finding that cost efficiency is positively associated with revenue generation ($\frac{Total\ Revenue}{Total\ Assets}$). The previous finding of greater capitalization being associated with more cost efficiency is also confirmed across methods and settings, although DEA is uninformative in Panels A and B ($\frac{Equity}{Total\ Assets}$). Furthermore, the surprising finding that more cost-efficient banks are not more value-creating, neither contemporaneously nor in the future, is also robust ($\frac{EVA}{Total\ Assets}$). This robustness also extends to the components of EVA, economic profits and the capital charge. Furthermore, the finding that more cost-efficient banks prefer to hold greater quantities of liquid assets is likewise confirmed.

Given this extensive analysis of cost efficiency, several salient points emerge. First, all three methods, SFA, DEA and GFA, produce reasonably similar statistical properties, possibly with the exception of the positive skewness exhibited by DEA. Second, I obtain plausible and robust associations with a comprehensive set of nonfrontier performance measures. This validates the information content of the efficiency measures. Third, the GFA method is the most informative across the majority of analyses and nonfrontier criteria. Given that it is both nonparametric and stochastic, that is, it combines the advantages of SFA and DEA without inheriting their drawbacks, this may not come as a surprise. Nonetheless, this finding represents an additional, important vindication of GFA.

Table A.18.: Correlation of Bank Cost Efficiency with Leading Nonfrontier Performance Measures.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the full population as well as split by size into the smallest 50%, the medium 40% and the largest 10% of banks. The correlation is between efficiency in period t and nonfrontier indicators in period $t+1$. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. DEA indicates data envelopment analysis. GFA indicates generalized frontier analysis (asymmetry parameter $b = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A:			*Panel B:*			*Panel C:*			*Panel D:*		
			All Banks			*Small Banks*			*Medium Banks*			*Large Banks*	
						0-50%			*50-90%*			*90-100%*	
Correlates		**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**
ROA	+	-0.0037	0.1852***	0.0519**	0.1430*	0.1913**	0.2128***	0.1365**	0.1398**	0.2811***	0.0577	0.0695	0.1407
$\frac{Total\ Cost}{Total\ Assets}$	−	-0.2164***	-0.6223***	-0.2144***	-0.4754***	-0.5284***	-0.1132**	-0.5928***	-0.5232***	-0.3320**	-0.4757***	-0.5019***	-0.3533***
$\frac{Total\ Revenue}{Total\ Assets}$	±	-0.0247	0.1466**	0.0219*	-0.0132	0.1048*	0.2093*	0.0139	0.1200**	0.1238**	0.0154	0.0521	0.0134
$\frac{Equity}{Total\ Assets}$	±	0.1386***	0.0019	0.2410***	0.0117	0.0594	-0.2071**	-0.0060	-0.0475	0.02300	0.0358	-0.0937	0.0986
$\frac{EVA}{Total\ Assets}$	±	-0.1949**	-0.0554	-0.2124**	0.0011	-0.0175*	0.1914*	-0.0100	-0.0015	0.1021*	0.0075	-0.0650	0.0053
$\frac{EP}{Total\ Assets}$	+	-0.0819***	-0.1101**	-0.0529	-0.0408	-0.0282	0.0883	-0.0553	-0.0274	0.0906**	-0.0057	-0.0722	0.0398
$\frac{Cap.\ Charge}{Total\ Assets}$	−	-0.3710***	0.1137	-0.7947***	-0.0382	-0.0857***	0.3389***	-0.0528*	-0.0122	0.2674*	-0.1271**	0.1288*	-0.2846***
$\frac{Liquid\ Assets}{Total\ Assets}$	±	0.0888***	-0.1077***	0.2061***	-0.0057	-0.0399	-0.3059***	-0.0288	-0.1314***	-0.1282***	-0.0318	-0.0942	-0.0636
$\frac{Nonp.\ Loans}{Total\ Loans}$	−	-0.0333	-0.0795*	0.0061	-0.0998***	-0.0942***	0.0086	-0.1009**	-0.0845*	0.0092	-0.0693	-0.0413	-0.0397

Table A.19.: Correlation of Bank Cost Efficiency with Nonfrontier Performance Measures, Balanced Sample.

This table reports Spearman rank correlations between different efficiency measures and nonfrontier indicators of performance for the population of banks. Panel A shows results for contemporaneous nonfrontier indicators. In Panel B the correlation is between efficiency in period t and nonfrontier indicators in period $t+1$. Panel C reports the correlation between the time series average of efficiency scores and the corresponding average of nonfrontier indicators. Stars indicate significance levels at 0.01 (***), 0.05 (**) and 0.1 (*) levels. SFA indicates stochastic frontier analysis. DEA indicates data envelopment analysis. GFA indicates generalized frontier analysis (asymmetry parameter $b = 1000$). ROA represents return on assets, EP denotes economic profit, EVA denotes economic value added.

		Panel A: Contemporaneous			*Panel B: Leading*			*Panel C: Average*		
Correlates		**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**	**SFA**	**DEA**	**GFA**
ROA	+	0.0765	0.1471***	0.1298*	0.0539	0.1562***	0.0892	0.0708***	0.1543***	0.0966***
$\frac{Total\ Cost}{Total\ Assets}$	−	-0.2994***	-0.6609***	-0.3542***	-0.2701***	-0.6217***	-0.3113***	-0.3205***	-0.7017***	-0.3534***
$\frac{Total\ Revenue}{Total\ Assets}$	±	-0.0073	0.0587	0.0390	-0.0064	0.0517	0.0363	-0.0099	0.0763***	0.0605***
$\frac{Equity}{Total\ Assets}$	±	0.1048***	0.0072	0.2823***	0.1054***	0.0366	0.2722***	0.1319***	0.0754***	0.3242***
$\frac{EVA}{Total\ Assets}$	±	-0.1268*	-0.0684	-0.2711***	-0.1319**	-0.0669	-0.2676***	-0.2257***	-0.1317***	-0.3739***
$\frac{EP}{Total\ Assets}$	+	-0.0738**	-0.1200***	-0.0876*	-0.0692**	-0.1120***	-0.0878*	-0.1275***	-0.1663***	-0.1248***
$\frac{CapitalCharge}{Total\ Assets}$	−	-0.2683***	0.0551	-0.7831***	-0.2687***	0.0546	-0.7890***	-0.3315***	0.0641***	-0.8811***
$\frac{Liquid\ Assets}{Total\ Assets}$	±	0.0668*	0.0193	0.2044***	0.0652	0.0169	0.2038***	0.0959***	0.0034	0.2526***
$\frac{Nonperf.\ Loans}{Total\ Loans}$	−	-0.0275	-0.1156***	0.0240	-0.0333	-0.0960**	0.0280	-0.0358	-0.1598***	0.0314

B. Appendix to Chapter 4

This appendix provides further evidence regarding the results in Chapter 4. Specifically, Section B.1 tabulates the results that have been discussed in Section 4.5 of the main analysis. Section B.2 tabulates and discusses results regarding the robustness checks. These robustness checks support the conclusions drawn in the main analysis.

B.1. Additional Analysis

This Section contains the tables that support the conclusions drawn in Section 4.5. Section B.1.1 investigates results that obtain when the sample is split by opacity. It reports results using both SFA and GFA as well as using the $CATFAT$ and $CATNONFAT$ measures of liquidity creation as the basis for intermediation quality.[1] These analyses report only the coefficients on the main variables of interest (opacity and fragility proxies) to conserve space. As the results are discussed in Section 4.5 at length, I merely provide the tabulations in the following. Furthermore, Section B.1.2 considers the effects of using a measure of intermediation quantity that follows Deep and Schaefer (2004) as the dependent variable.

B.1.1. Split Sample Analysis by Opacity

B.1.1.1. Sample Split by $OOAJLY$

[1]The main analysis for $CATNONFAT$ is replicated in the robustness checks (Section B.2.1).

Table B.1.: Intermediation Quality and Opacity, Split Sample Analysis by $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT					
Panel A1: 1st Quartile			*Panel A2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
3.834***	0.306***	1.437***	-0.425***	-0.0429**	0.598***
(10.90)	(13.23)	(4.14)	(-7.52)	(-2.26)	(5.83)

Panel B: GFA, CATFAT					
Panel B1: 1st Quartile			*Panel B2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.648***	-0.0652***	-0.439***	-0.0824***	-0.0596***	-0.0766**
(7.88)	(-11.69)	(-4.50)	(-3.00)	(-8.03)	(-2.05)

Panel C: SFA, CATNONFAT					
Panel C1: 1st Quartile			*Panel C2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
2.446***	0.221***	1.341***	-0.349***	-0.0217	0.656***
(9.00)	(12.97)	(5.19)	(-6.05)	(-1.28)	(6.72)

Panel D: GFA, CATNONFAT					
Panel D1: 1st Quartile			*Panel D2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.238***	0.0337***	0.325***	-0.155***	0.00128	0.213***
(3.43)	(7.30)	(4.56)	(-6.11)	(0.18)	(5.78)

Table B.2.: Intermediation Quality and Fragility, Split Sample Analysis by $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT											
Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.412***	0.0118***	0.117	0.501***	-0.00242***	-0.00687***	-0.265***	-0.00114	0.124	0.383***	-0.000564	0.00103*
(-24.27)	(12.37)	(0.63)	(26.34)	(-5.62)	(-12.57)	(-14.25)	(-1.55)	(1.42)	(17.81)	(-0.80)	(1.90)
Panel B: GFA, CATFAT											
Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0677***	0.00413***	-0.118***	0.0791***	-0.000751***	-0.00191***	-0.100***	0.00347***	0.0962***	0.132***	-0.000588**	-0.00212***
(-20.09)	(21.14)	(-2.93)	(18.50)	(-5.15)	(-19.77)	(-17.68)	(14.41)	(3.24)	(19.15)	(-1.98)	(-13.59)
Panel C: SFA, CATNONFAT											
Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.288***	0.00942***	-0.0316	0.342***	-0.00180***	-0.00579***	-0.198***	-0.000754	0.218***	0.272***	-0.000441	0.000660
(-21.93)	(13.03)	(-0.24)	(23.59)	(-5.36)	(-13.62)	(-12.47)	(-1.19)	(3.30)	(14.05)	(-0.71)	(1.34)
Panel D: GFA, CATNONFAT											
Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0687***	0.00253***	-0.0122	0.0798***	-0.000455***	-0.00128***	-0.103***	0.00106***	0.161***	0.122***	-0.000364	-0.000643***
(-21.99)	(14.05)	(-0.33)	(21.56)	(-4.63)	(-13.53)	(-18.76)	(4.47)	(5.36)	(17.90)	(-1.42)	(-4.39)

Table B.3.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OOAJLY$, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

						Panel A: SFA, CATFAT						
			Panel A1: 1^{st} Quartile							*Panel A2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	2.346***	3.482***	3.831***	2.791***	4.077***	3.322***	-0.302***	-0.431***	-0.425***	-0.401***	-0.422***	-0.442***
	(7.74)	(10.43)	(10.91)	(8.96)	(11.36)	(10.05)	(-5.51)	(-7.64)	(-7.53)	(-7.50)	(-7.45)	(-7.87)
Fragility	-0.401***	0.0112***	0.0477	0.489***	-0.00233***	-0.00652***	-0.246***	-0.00162**	0.139	0.379***	-0.00103	0.00163***
	(-24.00)	(12.15)	(0.26)	(26.21)	(-5.47)	(-12.23)	(-13.41)	(-2.23)	(1.60)	(18.09)	(-1.46)	(3.04)
						Panel B: GFA, CATFAT						
			Panel B1: 1^{st} Quartile							*Panel B2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.403***	0.520***	0.655***	0.483***	0.652***	0.502***	-0.0335	-0.0698**	-0.0829***	-0.0742***	-0.0743***	-0.0612**
	(4.79)	(6.42)	(7.97)	(5.86)	(7.75)	(6.13)	(-1.26)	(-2.51)	(-3.02)	(-2.88)	(-2.70)	(-2.18)
Fragility	-0.0658***	0.00406***	-0.130***	0.0770***	-0.000737***	-0.00186***	-0.0983***	0.00340***	0.0992***	0.132***	-0.000670**	-0.00204***
	(-19.12)	(20.69)	(-3.24)	(17.82)	(-5.11)	(-19.10)	(-18.02)	(13.81)	(3.35)	(19.21)	(-2.23)	(-12.36)
						Panel C: SFA, CATNONFAT						
			Panel C1: 1^{st} Quartile							*Panel C2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	1.400***	2.160***	2.450***	1.731***	2.600***	2.008***	-0.258***	-0.353***	-0.350***	-0.332***	-0.349***	-0.361***
	(5.74)	(8.33)	(9.03)	(6.96)	(9.37)	(7.80)	(-4.60)	(-6.13)	(-6.07)	(-5.91)	(-5.99)	(-6.29)
Fragility	-0.282***	0.00911***	-0.0758	0.335***	-0.00174***	-0.00557***	-0.183***	-0.00114*	0.230***	0.269***	-0.000827	0.00115**
	(-21.58)	(12.81)	(-0.57)	(23.32)	(-5.20)	(-13.33)	(-11.80)	(-1.83)	(3.51)	(14.19)	(-1.33)	(2.38)
						Panel D: GFA, CATNONFAT						
			Panel D1: 1^{st} Quartile							*Panel D2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	-0.0175	0.159**	0.239***	0.0680	0.256***	0.138**	-0.107***	-0.151***	-0.156***	-0.147***	-0.156***	-0.150***
	(-0.26)	(2.31)	(3.44)	(1.02)	(3.65)	(1.99)	(-4.40)	(-5.92)	(-6.15)	(-6.15)	(-6.16)	(-5.81)
Fragility	-0.0687***	0.00250***	-0.0165	0.0795***	-0.000449***	-0.00127***	-0.0968***	0.000892***	0.167***	0.121***	-0.000537**	-0.000438***
	(-21.70)	(13.77)	(-0.44)	(21.33)	(-4.57)	(-13.18)	(-18.31)	(3.77)	(5.63)	(18.14)	(-2.10)	(-2.90)

Table B.4.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OOAJLY$, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1^{st} Quartile						*Panel A2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0741***	0.281***	0.309***	0.0772***	0.301***	0.276***	-0.142***	-0.0425**	-0.0439**	-0.217***	-0.0471**	-0.0418**
	(3.43)	(12.72)	(13.50)	(3.55)	(12.74)	(12.52)	(-7.69)	(-2.25)	(-2.32)	(-11.86)	(-2.46)	(-2.21)
Fragility	-0.390***	0.0105***	-0.274	0.471***	-0.00184***	-0.00616***	-0.298***	-0.00112	0.138	0.467***	-0.000682	0.000997*
	(-22.42)	(11.78)	(-1.50)	(24.78)	(-4.58)	(-12.00)	(-15.79)	(-1.52)	(1.60)	(21.07)	(-0.96)	(1.84)
	Panel B: GFA, CATFAT											
	Panel B1: 1^{st} Quartile						*Panel B2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.128***	-0.0757***	-0.0648***	-0.128***	-0.0666***	-0.0755***	-0.101***	-0.0607***	-0.0604***	-0.127***	-0.0593***	-0.0619***
	(-21.21)	(-14.07)	(-11.63)	(-21.16)	(-11.64)	(-13.94)	(-13.52)	(-8.12)	(-8.18)	(-17.78)	(-7.98)	(-8.26)
Fragility	-0.105***	0.00446***	-0.0361	0.128***	-0.000881***	-0.00210***	-0.124***	0.00351***	0.116***	0.182***	-0.000738**	-0.00217***
	(-28.56)	(22.75)	(-0.93)	(26.99)	(-6.05)	(-21.35)	(-21.45)	(14.63)	(4.00)	(26.34)	(-2.49)	(-13.89)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1^{st} Quartile						*Panel C2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0598***	0.201***	0.224***	0.0671***	0.220***	0.195***	-0.0955***	-0.0215	-0.0234	-0.144***	-0.0251	-0.0211
	(3.53)	(12.34)	(13.32)	(3.99)	(12.76)	(12.06)	(-5.53)	(-1.27)	(-1.38)	(-8.60)	(-1.48)	(-1.24)
Fragility	-0.271***	0.00856***	-0.315**	0.316***	-0.00137***	-0.00528***	-0.220***	-0.000743	0.225***	0.328***	-0.000504	0.000643
	(-19.45)	(12.38)	(-2.41)	(21.15)	(-4.34)	(-13.02)	(-13.43)	(-1.18)	(3.46)	(16.40)	(-0.81)	(1.30)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1^{st} Quartile						*Panel D2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.00868*	0.0280***	0.0343***	-0.00627	0.0330***	0.0277***	-0.0361***	0.000947	0.000114	-0.0517***	-0.000220	0.000605
	(-1.70)	(6.24)	(7.50)	(-1.28)	(7.14)	(6.15)	(-5.08)	(0.13)	(0.02)	(-7.43)	(-0.03)	(0.08)
Fragility	-0.0712***	0.00241***	-0.0555	0.0822***	-0.000391***	-0.00121***	-0.112***	0.00106***	0.161***	0.142***	-0.000365	-0.000643***
	(-20.19)	(13.35)	(-1.49)	(20.59)	(-4.02)	(-12.74)	(-19.66)	(4.45)	(5.41)	(20.56)	(-1.43)	(-4.36)

Table B.5.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OOAJLY$, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Flannery, Kwan and Nimalendran (2013). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

						Panel A: SFA, CATFAT						
	Panel A1: 1^{st} Quartile						*Panel A2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	-0.277	0.927***	1.431***	0.394	1.483***	0.737**	0.538***	0.624***	0.605***	0.499***	0.607***	0.605***
	(-0.90)	(2.83)	(4.13)	(1.26)	(4.16)	(2.26)	(5.44)	(5.78)	(5.86)	(5.01)	(5.81)	(5.56)
Fragility	-0.414***	0.0115***	0.0785	0.499***	-0.00238***	-0.00676***	-0.262***	0.000576	0.164*	0.379***	-0.000511	-0.0000909
	(-24.36)	(12.30)	(0.42)	(26.39)	(-5.53)	(-12.46)	(-14.26)	(0.75)	(1.86)	(17.84)	(-0.74)	(-0.16)
						Panel B: GFA, CATFAT						
	Panel B1: 1^{st} Quartile						*Panel B2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	-0.737***	-0.628***	-0.430***	-0.610***	-0.459***	-0.647***	-0.0999***	0.0907**	-0.0728*	-0.112***	-0.0778**	0.0793**
	(-7.67)	(-6.62)	(-4.41)	(-6.37)	(-4.60)	(-6.77)	(-2.83)	(2.37)	(-1.94)	(-3.21)	(-2.06)	(2.09)
Fragility	-0.0719***	0.00427***	-0.107***	0.0819***	-0.000765***	-0.00201***	-0.101***	0.00372***	0.0913***	0.133***	-0.000595**	-0.00227***
	(-20.72)	(21.59)	(-2.62)	(18.88)	(-5.25)	(-20.42)	(-17.78)	(14.93)	(3.02)	(19.44)	(-2.01)	(-14.21)
						Panel C: SFA, CATNONFAT						
	Panel C1: 1^{st} Quartile						*Panel C2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.149	0.934***	1.346***	0.632***	1.370***	0.753***	0.611***	0.710***	0.667***	0.586***	0.662***	0.700***
	(0.63)	(3.78)	(5.23)	(2.64)	(5.18)	(3.05)	(6.48)	(6.97)	(6.77)	(6.09)	(6.68)	(6.96)
Fragility	-0.287***	0.00922***	-0.0676	0.339***	-0.00176***	-0.00567***	-0.195***	0.00120*	0.262***	0.267***	-0.000384	-0.000638
	(-21.81)	(12.84)	(-0.51)	(23.49)	(-5.25)	(-13.40)	(-12.39)	(1.85)	(3.85)	(14.02)	(-0.64)	(-1.28)
						Panel D: GFA, CATNONFAT						
	Panel D1: 1^{st} Quartile						*Panel D2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.0411	0.215***	0.326***	0.160**	0.323***	0.195***	0.190***	0.298***	0.220***	0.182***	0.214***	0.295***
	(0.59)	(3.02)	(4.57)	(2.31)	(4.46)	(2.70)	(5.49)	(7.70)	(5.92)	(5.08)	(5.72)	(7.66)
Fragility	-0.0684***	0.00248***	-0.0209	0.0791***	-0.000446***	-0.00125***	-0.102***	0.00188***	0.176***	0.120***	-0.000346	-0.00119***
	(-21.59)	(13.62)	(-0.56)	(21.27)	(-4.53)	(-13.00)	(-18.87)	(7.61)	(5.73)	(18.01)	(-1.38)	(-7.85)

B.1.1.2. Sample Split by $OLNJLY$

Table B.6.: Intermediation Quality and Opacity, Split Sample Analysis by $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT					
Panel A1: 1st Quartile			*Panel A2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.131	0.724***	1.094***	-0.0939	0.0109	0.415***
(1.37)	(9.40)	(10.29)	(-1.61)	(0.49)	(4.98)
Panel B: GFA, CATFAT					
Panel B1: 1st Quartile			*Panel B2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
-0.0928***	0.00991	0.0859***	0.193***	-0.0659***	0.195***
(-3.48)	(0.52)	(2.92)	(5.28)	(-6.94)	(5.09)
Panel C: SFA, CATNONFAT					
Panel C1: 1st Quartile			*Panel C2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.119	0.670***	0.811***	-0.265***	0.000562	0.297***
(1.43)	(10.51)	(9.56)	(-4.35)	(0.03)	(3.56)
Panel D: GFA, CATNONFAT					
Panel D1: 1st Quartile			*Panel D2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
-0.0192	0.262***	0.288***	0.0246	-0.0338***	0.153***
(-0.66)	(12.52)	(10.17)	(0.77)	(-4.43)	(4.85)

Table B.7.: Intermediation Quality and Fragility, Split Sample Analysis by $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT											
Panel A1: 1^{st} Quartile						*Panel A2: 4^{th} Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.434***	0.00866***	0.917***	0.670***	-0.00321***	-0.00634***	-0.120***	0.000320	-0.954***	0.234***	0.000137	-0.000345
(-23.39)	(8.45)	(7.66)	(30.49)	(-3.94)	(-8.91)	(-8.05)	(0.53)	(-7.72)	(13.48)	(0.44)	(-0.94)
Panel B: GFA, CATFAT											
Panel B1: 1^{st} Quartile						*Panel B2: 4^{th} Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.124***	0.00483***	0.197***	0.167***	-0.00112***	-0.00282***	-0.0472***	0.00242***	-0.118***	0.0962***	-0.000435**	-0.00130***
(-32.29)	(21.16)	(6.32)	(32.91)	(-5.28)	(-20.78)	(-8.60)	(9.75)	(-2.84)	(14.49)	(-2.24)	(-9.49)
Panel C: SFA, CATNONFAT											
Panel C1: 1^{st} Quartile						*Panel C2: 4^{th} Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.298***	0.00781***	0.691***	0.487***	-0.00243***	-0.00573***	-0.127***	0.00156***	-0.524***	0.143***	-0.000147	-0.00124***
(-19.66)	(9.36)	(8.00)	(26.75)	(-3.85)	(-9.54)	(-9.82)	(3.07)	(-5.57)	(8.91)	(-0.55)	(-3.82)
Panel D: GFA, CATNONFAT											
Panel D1: 1^{st} Quartile						*Panel D2: 4^{th} Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0968***	0.00268***	0.366***	0.159***	-0.000968***	-0.00141***	-0.0486***	0.00142***	-0.190***	0.0469***	-0.0000903	-0.000848***
(-23.90)	(10.82)	(10.68)	(31.18)	(-4.20)	(-9.04)	(-10.80)	(7.06)	(-5.01)	(8.30)	(-0.86)	(-7.55)

Table B.8.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OLNJLY$, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.245***	0.169*	0.116	0.0962	0.153	0.189*	-0.0711	-0.0931	-0.0779	-0.128**	-0.0753	-0.0922
	(2.84)	(1.72)	(1.22)	(1.16)	(1.60)	(1.90)	(-1.22)	(-1.59)	(-1.33)	(-2.25)	(-1.31)	(-1.58)
Fragility	-0.437***	0.00878***	0.907***	0.669***	-0.00310***	-0.00646***	-0.119***	0.000259	-0.942***	0.237***	0.0000952	-0.000305
	(-23.55)	(8.51)	(7.53)	(30.43)	(-3.84)	(-9.04)	(-8.02)	(0.43)	(-7.55)	(13.61)	(0.31)	(-0.83)
	Panel B: GFA, CATFAT											
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	-0.0606***	-0.0721***	-0.0962***	-0.102***	-0.0875***	-0.0679**	0.203***	0.201***	0.196***	0.180***	0.206***	0.201***
	(-2.64)	(-2.67)	(-3.63)	(-4.39)	(-3.32)	(-2.53)	(5.65)	(5.40)	(5.33)	(5.08)	(5.57)	(5.44)
Fragility	-0.123***	0.00478***	0.205***	0.167***	-0.00118***	-0.00278***	-0.0518***	0.00255***	-0.149***	0.0919***	-0.000321*	-0.00139***
	(-32.59)	(20.66)	(6.52)	(33.14)	(-5.52)	(-20.06)	(-9.88)	(10.34)	(-3.55)	(13.41)	(-1.72)	(-10.29)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.198**	0.154*	0.108	0.0939	0.136	0.171**	-0.242***	-0.261***	-0.257***	-0.286***	-0.262***	-0.259***
	(2.54)	(1.80)	(1.30)	(1.23)	(1.61)	(1.98)	(-4.05)	(-4.29)	(-4.21)	(-4.74)	(-4.30)	(-4.27)
Fragility	-0.301***	0.00792***	0.682***	0.486***	-0.00233***	-0.00583***	-0.121***	0.00139***	-0.484***	0.149***	-0.000292	-0.00113***
	(-19.87)	(9.48)	(7.84)	(26.68)	(-3.72)	(-9.76)	(-9.74)	(2.75)	(-5.12)	(9.70)	(-1.10)	(-3.52)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.00615	-0.00760	-0.0253	-0.0275	-0.0190	-0.00657	0.0340	0.0288	0.0279	0.0179	0.0281	0.0294
	(0.24)	(-0.26)	(-0.88)	(-1.08)	(-0.66)	(-0.22)	(1.09)	(0.90)	(0.87)	(0.57)	(0.87)	(0.92)
Fragility	-0.0969***	0.00267***	0.369***	0.159***	-0.000981***	-0.00141***	-0.0493***	0.00144***	-0.195***	0.0465***	-0.0000747	-0.000861***
	(-24.15)	(10.72)	(10.68)	(31.23)	(-4.25)	(-8.94)	(-11.43)	(7.13)	(-5.08)	(8.11)	(-0.72)	(-7.66)

Table B.9.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OLNJLY$, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

						Panel A: SFA, CATFAT						
			Panel A1: 1^{st} Quartile							*Panel A2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.584***	0.728***	0.725***	0.274***	0.682***	0.714***	-0.0566**	0.0108	0.0248	-0.0872***	0.0125	0.0107
	(8.26)	(9.60)	(9.50)	(4.07)	(8.61)	(9.47)	(-2.36)	(0.48)	(1.15)	(-3.78)	(0.56)	(0.48)
Fragility	-0.425***	0.00870***	0.921***	0.655***	-0.00330***	-0.00627***	-0.136***	0.000314	-0.969***	0.259***	0.000155	-0.000343
	(-23.20)	(8.64)	(7.84)	(29.91)	(-4.08)	(-8.97)	(-8.43)	(0.52)	(-8.03)	(14.27)	(0.51)	(-0.93)
						Panel B: GFA, CATFAT						
			Panel B1: 1^{st} Quartile							*Panel B2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0313*	0.0119	0.0101	-0.108***	0.00570	0.00530	-0.103***	-0.0673***	-0.0648***	-0.115***	-0.0669***	-0.0668***
	(-1.88)	(0.66)	(0.53)	(-6.46)	(0.29)	(0.30)	(-9.80)	(-7.06)	(-6.91)	(-11.68)	(-6.94)	(-7.02)
Fragility	-0.125***	0.00483***	0.197***	0.172***	-0.00112***	-0.00282***	-0.0755***	0.00246***	-0.0778*	0.130***	-0.000530***	-0.00132***
	(-32.39)	(21.18)	(6.32)	(33.73)	(-5.29)	(-20.77)	(-12.29)	(9.96)	(-1.96)	(18.57)	(-2.71)	(-9.60)
						Panel C: SFA, CATNONFAT						
			Panel C1: 1^{st} Quartile							*Panel C2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.574***	0.673***	0.671***	0.348***	0.639***	0.660***	-0.0722***	-0.000348	0.00810	-0.0602***	0.00756	-0.000317
	(9.55)	(10.77)	(10.62)	(6.04)	(9.77)	(10.61)	(-3.56)	(-0.02)	(0.47)	(-3.01)	(0.43)	(-0.02)
Fragility	-0.290***	0.00785***	0.695***	0.468***	-0.00252***	-0.00566***	-0.146***	0.00156***	-0.529***	0.161***	-0.000137	-0.00124***
	(-19.35)	(9.62)	(8.16)	(25.83)	(-4.04)	(-9.66)	(-9.96)	(3.06)	(-5.78)	(8.91)	(-0.51)	(-3.81)
						Panel D: GFA, CATNONFAT						
			Panel D1: 1^{st} Quartile							*Panel D2: 4^{th} Quartile*		
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.231***	0.263***	0.263***	0.159***	0.256***	0.260***	-0.0671***	-0.0346***	-0.0314***	-0.0580***	-0.0323***	-0.0344***
	(11.64)	(12.83)	(12.67)	(8.21)	(11.92)	(12.63)	(-8.09)	(-4.58)	(-4.24)	(-7.26)	(-4.26)	(-4.56)
Fragility	-0.0936***	0.00269***	0.368***	0.150***	-0.00100***	-0.00138***	-0.0670***	0.00144***	-0.171***	0.0641***	-0.000136	-0.000857***
	(-23.26)	(11.15)	(10.89)	(29.60)	(-4.45)	(-9.14)	(-13.84)	(7.22)	(-4.77)	(11.04)	(-1.31)	(-7.71)

Table B.10.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OLNJLY$, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Flannery, Kwan and Nimalendran (2013). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.777***	1.262***	1.094***	0.658***	1.111***	1.238***	0.353***	0.419***	0.445***	0.286***	0.455***	0.420***
	(8.28)	(11.58)	(10.35)	(7.10)	(10.17)	(11.42)	(4.20)	(5.04)	(5.39)	(3.42)	(5.38)	(5.05)
Fragility	-0.424***	0.00997***	0.916***	0.656***	-0.00284***	-0.00697***	-0.115***	0.000515	-0.987***	0.227***	0.000254	-0.000435
	(-23.15)	(9.71)	(7.72)	(30.27)	(-3.60)	(-9.93)	(-7.59)	(0.86)	(-8.02)	(12.94)	(0.83)	(-1.20)
	Panel B: GFA, CATFAT											
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	-0.00704	0.170***	0.0858***	-0.0252	0.0798***	0.146***	0.171***	0.216***	0.200***	0.143***	0.199***	0.210***
	(-0.28)	(6.11)	(2.94)	(-0.99)	(2.63)	(5.27)	(4.37)	(5.71)	(5.21)	(3.71)	(5.10)	(5.56)
Fragility	-0.124***	0.00501***	0.197***	0.167***	-0.00109***	-0.00289***	-0.0444***	0.00252***	-0.133***	0.0927***	-0.000384**	-0.00134***
	(-32.29)	(22.13)	(6.34)	(32.85)	(-5.20)	(-21.57)	(-7.89)	(10.31)	(-3.24)	(13.85)	(-2.00)	(-9.94)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.594***	0.960***	0.811***	0.495***	0.818***	0.940***	0.230***	0.310***	0.313***	0.218***	0.313***	0.310***
	(7.55)	(11.13)	(9.62)	(6.39)	(9.41)	(10.87)	(2.74)	(3.75)	(3.79)	(2.61)	(3.66)	(3.77)
Fragility	-0.291***	0.00881***	0.691***	0.476***	-0.00216***	-0.00620***	-0.123***	0.00171***	-0.547***	0.137***	-0.0000664	-0.00130***
	(-19.30)	(10.60)	(8.06)	(26.39)	(-3.52)	(-10.53)	(-9.24)	(3.39)	(-5.85)	(8.64)	(-0.25)	(-4.07)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.218***	0.340***	0.288***	0.185***	0.285***	0.321***	0.127***	0.165***	0.159***	0.128***	0.158***	0.162***
	(8.40)	(12.15)	(10.25)	(7.27)	(9.74)	(11.48)	(4.02)	(5.32)	(5.13)	(4.03)	(4.93)	(5.26)
Fragility	-0.0941***	0.00303***	0.366***	0.155***	-0.000873***	-0.00157***	-0.0465***	0.00149***	-0.202***	0.0438***	-0.0000495	-0.000883***
	(-23.44)	(12.49)	(10.81)	(30.73)	(-3.89)	(-10.39)	(-10.08)	(7.54)	(-5.38)	(7.73)	(-0.48)	(-7.90)

B.1.1.3. Sample Split by $OPQFKN$

Table B.11.:
Intermediation Quality and Opacity, Split Sample Analysis by $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT					
Panel A1: 1st Quartile			*Panel A2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
-0.424***	0.293***	3.813***	-0.216***	-0.0315*	0.323***
(-2.80)	(12.56)	(7.77)	(-3.54)	(-1.78)	(3.21)

Panel B: GFA, CATFAT					
Panel B1: 1st Quartile			*Panel B2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
-0.143***	-0.0550***	0.272**	-0.0144	-0.0625***	-0.195***
(-2.75)	(-9.22)	(2.52)	(-0.44)	(-9.45)	(-5.54)

Panel C: SFA, CATNONFAT					
Panel C1: 1st Quartile			*Panel C2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
-0.434***	0.205***	2.676***	-0.153**	-0.0189	0.367***
(-3.13)	(11.64)	(7.27)	(-2.34)	(-1.29)	(3.67)

Continued on next page

Table B.11 – *Continued from previous page*

Panel D: GFA, CATNONFAT

Panel D1: 1st Quartile			*Panel D2: 4th Quartile*		
OOAJLY	*OLNJLY*	*OPQFKN*	*OOAJLY*	*OLNJLY*	*OPQFKN*
-0.233***	0.0334***	0.487***	-0.0998***	-0.00986*	-0.0388
(-4.98)	(6.43)	(4.51)	(-3.40)	(-1.70)	(-1.16)

Table B.12.: Intermediation Quality and Fragility, Split Sample Analysis by $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT											
Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.418***	0.0110***	0.376**	0.514***	-0.00267***	-0.00637***	-0.247***	-0.000753	-0.106	0.363***	-0.000100	0.000506
(-24.20)	(11.37)	(2.38)	(26.29)	(-5.48)	(-11.43)	(-14.76)	(-1.06)	(-1.20)	(19.09)	(-0.16)	(0.99)
Panel B: GFA, CATFAT											
Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0738***	0.00406***	-0.0157	0.0865***	-0.000644***	-0.00187***	-0.0896***	0.00369***	0.0470	0.114***	-0.000599**	-0.00221***
(-19.37)	(20.36)	(-0.43)	(18.82)	(-4.81)	(-19.11)	(-20.20)	(16.10)	(1.59)	(20.08)	(-2.23)	(-15.07)
Panel C: SFA, CATNONFAT											
Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.287***	0.00887***	0.126	0.343***	-0.00192***	-0.00546***	-0.178***	-0.000248	0.0423	0.254***	-0.0000165	0.0000809
(-21.45)	(12.02)	(1.14)	(22.94)	(-5.09)	(-12.61)	(-12.70)	(-0.42)	(0.62)	(15.00)	(-0.03)	(0.18)
Panel D: GFA, CATNONFAT											
Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0749***	0.00244***	0.0996***	0.0875***	-0.000462***	-0.00115***	-0.0826***	0.00155***	0.110***	0.0996***	-0.0000394	-0.000950***
(-20.61)	(12.38)	(2.59)	(20.34)	(-4.17)	(-11.41)	(-19.54)	(7.49)	(3.73)	(18.85)	(-0.21)	(-7.75)

Table B.13.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OPQFKN$, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

						Panel A: SFA, CATFAT						
			Panel A1: 1st Quartile						*Panel A2: 4th Quartile*			
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
OOAJLY	-0.242*	-0.461***	-0.432***	-0.344***	-0.394**	-0.441***	-0.103*	-0.228***	-0.214***	-0.242***	-0.218***	-0.237***
	(-1.88)	(-3.08)	(-2.87)	(-2.71)	(-2.53)	(-2.94)	(-1.68)	(-3.73)	(-3.50)	(-3.89)	(-3.55)	(-3.87)
Fragility	-0.416***	0.0111***	0.411***	0.513***	-0.00276***	-0.00640***	-0.243***	-0.00125*	-0.0783	0.365***	-0.000330	0.000957*
	(-24.12)	(11.55)	(2.59)	(26.39)	(-5.63)	(-11.48)	(-14.42)	(-1.73)	(-0.88)	(19.23)	(-0.53)	(1.85)
						Panel B: GFA, CATFAT						
			Panel B1: 1st Quartile						*Panel B2: 4th Quartile*			
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
OOAJLY	-0.111**	-0.156***	-0.143***	-0.129***	-0.129**	-0.148***	0.0277	0.0237	-0.0154	-0.0225	-0.00710	0.0364
	(-2.36)	(-2.97)	(-2.74)	(-2.75)	(-2.49)	(-2.82)	(0.85)	(0.73)	(-0.47)	(-0.71)	(-0.22)	(1.10)
Fragility	-0.0727***	0.00411***	-0.00419	0.0858***	-0.000673***	-0.00188***	-0.0906***	0.00374***	0.0490*	0.114***	-0.000607**	-0.00228***
	(-20.12)	(20.61)	(-0.11)	(19.20)	(-4.96)	(-19.13)	(-20.82)	(15.34)	(1.66)	(20.25)	(-2.26)	(-14.09)
						Panel C: SFA, CATNONFAT						
			Panel C1: 1st Quartile						*Panel C2: 4th Quartile*			
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
OOAJLY	-0.310**	-0.464***	-0.437***	-0.381***	-0.420***	-0.449***	-0.0714	-0.159**	-0.154**	-0.171**	-0.157**	-0.161**
	(-2.46)	(-3.37)	(-3.16)	(-3.08)	(-3.00)	(-3.25)	(-1.11)	(-2.42)	(-2.36)	(-2.56)	(-2.36)	(-2.46)
Fragility	-0.284***	0.00900***	0.161	0.341***	-0.00201***	-0.00549***	-0.175***	-0.000590	0.0621	0.256***	-0.000182	0.000388
	(-21.49)	(12.25)	(1.45)	(23.17)	(-5.31)	(-12.67)	(-12.71)	(-1.00)	(0.92)	(15.19)	(-0.34)	(0.87)
						Panel D: GFA, CATNONFAT						
			Panel D1: 1st Quartile						*Panel D2: 4th Quartile*			
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
OOAJLY	-0.201***	-0.241***	-0.235***	-0.220***	-0.233***	-0.236***	-0.0626**	-0.0859***	-0.102***	-0.107***	-0.102***	-0.0821***
	(-4.80)	(-5.11)	(-5.05)	(-5.20)	(-4.82)	(-5.00)	(-2.19)	(-2.85)	(-3.48)	(-3.73)	(-3.46)	(-2.68)
Fragility	-0.0730***	0.00250***	0.119***	0.0864***	-0.000515***	-0.00117***	-0.0802***	0.00136***	0.123***	0.101***	-0.000147	-0.000794***
	(-21.62)	(12.99)	(3.09)	(21.37)	(-4.59)	(-11.60)	(-19.34)	(6.25)	(4.21)	(19.26)	(-0.78)	(-5.82)

Table B.14.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OPQFKN$, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

						Panel A: SFA, CATFAT						
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0670***	0.273***	0.292***	0.0569***	0.287***	0.269***	-0.123***	-0.0310*	-0.0307*	-0.198***	-0.0337*	-0.0308*
	(3.05)	(12.20)	(12.59)	(2.58)	(12.00)	(12.02)	(-7.25)	(-1.75)	(-1.74)	(-11.55)	(-1.87)	(-1.74)
Fragility	-0.399***	0.0100***	0.144	0.493***	-0.00209***	-0.00577***	-0.276***	-0.000707	-0.0912	0.441***	-0.000175	0.000470
	(-22.54)	(10.92)	(0.92)	(24.83)	(-4.62)	(-10.98)	(-16.24)	(-0.99)	(-1.04)	(22.32)	(-0.28)	(0.92)
						Panel B: GFA, CATFAT						
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.115***	-0.0634***	-0.0553***	-0.118***	-0.0560***	-0.0635***	-0.100***	-0.0656***	-0.0632***	-0.124***	-0.0621***	-0.0661***
	(-16.94)	(-10.86)	(-9.24)	(-18.09)	(-9.14)	(-10.83)	(-14.70)	(-9.97)	(-9.62)	(-18.59)	(-9.33)	(-9.99)
Fragility	-0.106***	0.00429***	0.0284	0.131***	-0.000756***	-0.00201***	-0.113***	0.00379***	0.0768***	0.163***	-0.000736***	-0.00229***
	(-24.78)	(21.33)	(0.80)	(25.76)	(-5.55)	(-20.13)	(-24.37)	(16.58)	(2.70)	(28.33)	(-2.70)	(-15.59)
						Panel C: SFA, CATNONFAT						
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0500***	0.189***	0.205***	0.0491***	0.203***	0.183***	-0.0848***	-0.0187	-0.0194	-0.135***	-0.0210	-0.0188
	(2.80)	(11.13)	(11.73)	(2.79)	(11.40)	(10.87)	(-5.78)	(-1.27)	(-1.32)	(-9.32)	(-1.40)	(-1.27)
Fragility	-0.273***	0.00821***	-0.0376	0.325***	-0.00151***	-0.00505***	-0.198***	-0.000220	0.0515	0.308***	-0.0000628	0.0000589
	(-19.20)	(11.54)	(-0.34)	(20.82)	(-4.26)	(-12.15)	(-13.64)	(-0.37)	(0.77)	(17.43)	(-0.12)	(0.13)
						Panel D: GFA, CATNONFAT						
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0107*	0.0289***	0.0328***	-0.0103*	0.0320***	0.0288***	-0.0405***	-0.0111*	-0.0109*	-0.0557***	-0.0102*	-0.0114**
	(-1.82)	(5.65)	(6.31)	(-1.85)	(6.15)	(5.62)	(-6.74)	(-1.93)	(-1.89)	(-9.44)	(-1.75)	(-1.98)
Fragility	-0.0779***	0.00233***	0.0735*	0.0914***	-0.000398***	-0.00109***	-0.0922***	0.00157***	0.115***	0.122***	-0.0000619	-0.000964***
	(-18.69)	(11.77)	(1.89)	(19.37)	(-3.67)	(-10.68)	(-20.46)	(7.53)	(4.01)	(22.13)	(-0.33)	(-7.81)

Table B.15.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by $OPQFKN$, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Flannery, Kwan and Nimalendran (2013). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	1.489***	3.230***	3.780***	2.244***	4.022***	3.026***	0.427***	0.321***	0.324***	0.318***	0.341***	0.323***
	(3.55)	(6.90)	(7.73)	(5.18)	(8.00)	(6.48)	(4.31)	(3.11)	(3.22)	(3.12)	(3.30)	(3.12)
Fragility	-0.412***	0.0105***	0.321**	0.506***	-0.00261***	-0.00605***	-0.250***	-0.0000364	-0.108	0.363***	-0.0000126	0.00000345
	(-23.98)	(11.05)	(2.05)	(26.14)	(-5.43)	(-11.02)	(-14.93)	(-0.05)	(-1.23)	(19.06)	(-0.02)	(0.01)
	Panel B: GFA, CATFAT											
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	-0.148	0.0468	0.274**	0.00417	0.264**	0.0293	-0.158***	-0.0183	-0.195***	-0.197***	-0.187***	-0.0115
	(-1.46)	(0.45)	(2.53)	(0.04)	(2.40)	(0.28)	(-4.61)	(-0.51)	(-5.55)	(-5.77)	(-5.20)	(-0.33)
Fragility	-0.0744***	0.00406***	-0.0196	0.0865***	-0.000640***	-0.00187***	-0.0884***	0.00365***	0.0486*	0.114***	-0.000648**	-0.00219***
	(-19.28)	(20.21)	(-0.54)	(18.65)	(-4.78)	(-18.89)	(-19.98)	(15.44)	(1.65)	(20.23)	(-2.40)	(-14.66)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	1.082***	2.202***	2.668***	1.631***	2.828***	1.994***	0.443***	0.398***	0.367***	0.363***	0.383***	0.414***
	(3.30)	(6.24)	(7.26)	(4.85)	(7.51)	(5.66)	(4.56)	(3.91)	(3.67)	(3.51)	(3.73)	(4.17)
Fragility	-0.283***	0.00853***	0.0871	0.337***	-0.00188***	-0.00525***	-0.182***	0.000639	0.0394	0.254***	0.0000820	-0.000564
	(-21.13)	(11.71)	(0.80)	(22.66)	(-5.04)	(-12.23)	(-12.95)	(1.07)	(0.58)	(14.95)	(0.15)	(-1.26)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.0661	0.355***	0.478***	0.219**	0.494***	0.342***	-0.00443	0.0407	-0.0394	-0.0403	-0.0318	0.0470
	(0.66)	(3.31)	(4.42)	(2.14)	(4.48)	(3.16)	(-0.14)	(1.17)	(-1.18)	(-1.19)	(-0.93)	(1.36)
Fragility	-0.0746***	0.00238***	0.0927**	0.0867***	-0.000455***	-0.00112***	-0.0825***	0.00164***	0.110***	0.0996***	-0.0000476	-0.00102***
	(-20.39)	(11.99)	(2.41)	(20.06)	(-4.14)	(-10.88)	(-19.53)	(7.61)	(3.74)	(18.89)	(-0.25)	(-8.07)

B.1.2. Analysis of an Alternative Measure of Bank Intermediation

This section provides results on the relation between opacity, fragility and intermediation in the case where bank intermediation is measured by the liquidity transformation gap of Deep and Schaefer (2004). Although this measure has some shortcomings in terms of measuring the liquidity created by banks, it also brings with it several advantages. First, it enables one to investigate the robustness of the results to both the choice of dependent variable (intermediation quality as proxied by liquidity efficiency in the main analysis) and the estimation method (Tobit in the main analysis). This is because it relies neither on efficiency nor on Tobit regressions but rather estimates a fixed effects model of the form

$$\begin{aligned} LTG_{i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,t,j} + \delta FRAG_{i,t,k} \\ &+ \sum_{t=1}^{17} \theta_t d_t + \nu_i + \epsilon_{i,t}, \end{aligned} \tag{B.1}$$

where LTG denotes the liquidity transformation gap scaled by total assets and all other variables are as previously defined. In the first instance, δ is constrained to zero for all k so as to investigate the results for opacity alone, which will allow one to distinguish A1/A2 from the null and A3. The findings are summarized in Table B.16. The control variables indicate similar relations as before, i.e. better intermediaries are smaller ($BKSIZE$) and more profitable (ROA). They operate in more populous and more affluent ($BKPOP, BKICHG$) markets and they are organized as holding companies ($MBHC, OBHC$). In contrast to previous results, better intermediaries are more cost efficient (CE) and operate in markets where larger banks are present ($BKMSML$). As regards the main variables of interest, these indicate that even in this changed scenario, opacity is significantly positively associated with intermediation for the $OLNJLY$ and $OPQFKN$ measures, while it is significantly negative for $OOAJLY$. Overall, this confirms the main results and leads to the rejection of the null as well as A3.

Table B.16.:
Intermediation and Opacity, Intermediation Measured by the LT-Gap of Deep and Schaefer (2004).

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is the LT-Gap of Deep and Schaefer (2004). Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Parameter	(1)	(2)	(3)
$OOAJLY$	-0.219***		
	(-7.46)		
$OLNJLY$		0.591***	
		(52.00)	
$OPQFKN$			0.0957**
			(2.08)
$BKSIZE$	-0.0313***	-0.0194***	-0.0334***
	(-11.61)	(-7.57)	(-12.33)
CE	0.198***	0.217***	0.185***
	(7.88)	(9.02)	(7.33)
ROA	2.047***	1.897***	2.230***
	(23.99)	(23.54)	(26.26)
$BKHHI$	-0.00773	-0.00902	-0.00793
	(-1.17)	(-1.47)	(-1.21)
$BKMSML$	0.0154***	0.0131***	0.0153***
	(4.04)	(3.66)	(4.03)
$BKPOP$	0.0198***	0.0204***	0.0194***
	(11.33)	(12.91)	(11.12)
$BKPDNS$	0.00190	0.00506	0.00107
	(0.47)	(1.33)	(0.26)
$BKICHG$	0.0228***	0.0241***	0.0243***
	(3.26)	(3.78)	(3.47)
$MBHC$	0.0190***	0.0108***	0.0154***
	(4.55)	(2.79)	(3.68)
$OBHC$	0.0268***	0.0200***	0.0262***

Continued on next page

Table B.16 – *Continued from previous page*

Parameter	(1)	(2)	(3)
	(8.11)	(6.50)	(7.93)
MRG	0.0282	0.0235	0.0235
	(0.75)	(0.52)	(0.62)
ACQ	-0.00434**	-0.00299	-0.00513***
	(-2.21)	(-1.61)	(-2.59)
Constant	-0.0170	-0.329***	0.0119
	(-0.42)	(-8.27)	(0.29)
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R^2	0.134	0.245	0.132
N	118164	118164	118164

The next step is to constrain γ to zero for all j so as to analyze the impact of fragility on intermediation. Table B.17 provides the results. As in the main analysis, I find that, overall, fragility exerts a positive influence on intermediation. Thus, banks that create more liquidity have fewer liquid assets, higher leverage and more risk weighted assets ($LAGTA$, $LEVRAG$ and $CREDRSK$). They also have a higher level of nonperforming loans (NPL) and lower distance to default ($ZIND_{pool}$). Overall, the evidence indicates that A1 should be rejected in favor of A2.

Table B.17.: Intermediation and Fragility, Intermediation Measured by the LT-Gap of Deep and Schaefer (2004).

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is the LT-Gap of Deep and Schaefer (2004). Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$LAGTA$	-0.880***					
	(-161.64)					
$LEVRAG$		0.00478***				
		(13.04)				
NPL			0.346***			
			(7.92)			
$CREDRSK$				0.494***		
				(64.36)		
$ZIND_{MA(3)}$					-0.000183	
					(-1.18)	
$ZIND_{pool}$						-0.00410***
						(-18.11)
$BKSIZE$	-0.0433***	-0.0356***	-0.0336***	-0.0489***	-0.0346***	-0.0349***
	(-23.17)	(-13.05)	(-12.38)	(-19.80)	(-11.95)	(-12.92)
CE	0.145***	0.221***	0.187***	0.212***	0.198***	0.238***
	(8.27)	(8.74)	(7.44)	(9.44)	(7.72)	(9.41)
ROA	1.166***	2.459***	2.459***	1.746***	2.144***	2.825***

Continued on next page

Table B.17 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
	(20.84)	(28.58)	(27.05)	(23.52)	(24.81)	(31.69)
$BKHHI$	0.00413	-0.00760	-0.00708	-0.00906	-0.00690	-0.00696
	(0.94)	(-1.16)	(-1.08)	(-1.52)	(-1.03)	(-1.07)
$BKMSML$	0.0105***	0.0158***	0.0163***	0.0167***	0.0143***	0.0148***
	(4.26)	(4.19)	(4.30)	(4.91)	(3.71)	(3.93)
$BKPOP$	0.00723***	0.0198***	0.0194***	0.0149***	0.0198***	0.0201***
	(6.61)	(11.47)	(11.11)	(9.79)	(11.13)	(11.68)
$BKPDNS$	-0.000489	0.00252	0.000769	-0.000435	0.00122	0.00324
	(-0.18)	(0.63)	(0.19)	(-0.12)	(0.29)	(0.81)
$BKICHG$	0.0763***	0.0188***	0.0289***	0.0506***	0.0281***	0.0153**
	(15.65)	(2.70)	(4.15)	(7.82)	(4.02)	(2.20)
$MBHC$	-0.00340	0.0154***	0.0162***	0.0116***	0.0171***	0.0149***
	(-1.25)	(3.73)	(3.87)	(3.13)	(3.94)	(3.65)
$OBHC$	0.00570***	0.0240***	0.0262***	0.0223***	0.0275***	0.0225***
	(2.63)	(7.32)	(7.93)	(7.54)	(7.99)	(6.97)
MRG	0.0357	0.0314	0.0246	0.0154	0.0300	0.0325
	(1.17)	(0.85)	(0.65)	(0.40)	(0.75)	(0.89)
ACQ	-0.00200	-0.00396**	-0.00481**	-0.00436**	-0.00506**	-0.00362*
	(-1.52)	(-2.03)	(-2.44)	(-2.53)	(-2.54)	(-1.87)
Constant	0.665***	-0.0486	0.00967	-0.0516	0.0123	0.0299
	(23.10)	(-1.20)	(0.24)	(-1.40)	(0.29)	(0.74)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.615	0.139	0.133	0.276	0.134	0.144
N	118164	118164	118164	118164	115003	118164

In order to investigate the robustness of the findings from the joint analysis of opacity and fragility, the third step of the analysis combines both of these variable sets. In other words, it allows both γ and δ to differ from zero in Equation B.1. These results are reported in Tables B.18-B.20. In line with the main results, findings suggest that both opacity and fragility proxies maintain their respective signs and significances. Specifically, $OOAJLY$ remains significantly negative, $OLNJLY$ significantly positive and $OPQFKN$ remains significantly positive in the majority of cases with the exception of the regressions where $LAGTA$ and $CREDRSK$ proxy for fragility. Taken together, this indicates that the influence of both opacity and fragility on bank intermediation is robust and thus increases the confidence with which A1 is rejected in favor of A2, the "Opacity-Fragility Hypothesis".

Table B.18.:

Intermediation, Opacity and Fragility, Intermediation Measured by the LT-Gap of Deep and Schaefer (2004), Opacity Based on $OOAJLY$.

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is the LT-Gap of Deep and Schaefer (2004). Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$OOAJLY$	-0.110***	-0.164***	-0.226***	-0.278***	-0.204***	-0.135***
	(-5.34)	(-5.51)	(-7.70)	(-10.06)	(-6.77)	(-4.52)
$LAGTA$	-0.879***					
	(-161.64)					
$LEVRAG$		0.00445***				
		(11.95)				
NPL			0.361***			
			(8.29)			
$CREDRSK$				0.497***		
				(64.74)		
$ZIND_{MA(3)}$					-0.000209	
					(-1.35)	
$ZIND_{pool}$						-0.00391***
						(-16.82)

Continued on next page

Table B.18 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$BKSIZE$	-0.0425***	-0.0342***	-0.0319***	-0.0469***	-0.0329***	-0.0337***
	(-22.64)	(-12.48)	(-11.75)	(-18.95)	(-11.37)	(-12.46)
CE	0.150***	0.226***	0.196***	0.224***	0.206***	0.241***
	(8.51)	(8.92)	(7.81)	(9.94)	(8.04)	(9.54)
ROA	1.093***	2.330***	2.318***	1.556***	2.009***	2.705***
	(19.33)	(26.31)	(25.28)	(20.65)	(22.88)	(29.16)
$BKHHI$	0.00413	-0.00759	-0.00702	-0.00904	-0.00686	-0.00698
	(0.94)	(-1.16)	(-1.07)	(-1.52)	(-1.02)	(-1.07)
$BKMSML$	0.0106***	0.0158***	0.0164***	0.0167***	0.0145***	0.0148***
	(4.26)	(4.18)	(4.31)	(4.92)	(3.73)	(3.94)
$BKPOP$	0.00741***	0.0201***	0.0197***	0.0153***	0.0201***	0.0202***
	(6.73)	(11.57)	(11.27)	(10.01)	(11.27)	(11.76)
$BKPDNS$	-0.000141	0.00295	0.00146	0.000431	0.00186	0.00357
	(-0.05)	(0.73)	(0.36)	(0.12)	(0.44)	(0.89)
$BKICHG$	0.0756***	0.0183***	0.0279***	0.0492***	0.0270***	0.0149**
	(15.56)	(2.63)	(4.02)	(7.65)	(3.88)	(2.16)
$MBHC$	-0.00208	0.0174***	0.0188***	0.0149***	0.0195***	0.0165***
	(-0.77)	(4.23)	(4.53)	(4.02)	(4.52)	(4.06)
$OBHC$	0.00591***	0.0244***	0.0265***	0.0228***	0.0279***	0.0229***
	(2.72)	(7.46)	(8.05)	(7.71)	(8.09)	(7.09)
MRG	0.0375	0.0336	0.0283	0.0200	0.0330	0.0344
	(1.24)	(0.92)	(0.75)	(0.53)	(0.83)	(0.94)
ACQ	-0.00172	-0.00360*	-0.00421**	-0.00362**	-0.00452**	-0.00333*
	(-1.31)	(-1.85)	(-2.14)	(-2.12)	(-2.28)	(-1.72)
Constant	0.653***	-0.0619	-0.0137	-0.0808**	-0.0101	0.0148
	(22.54)	(-1.53)	(-0.34)	(-2.18)	(-0.24)	(0.36)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.615	0.140	0.136	0.280	0.136	0.145
N	118164	118164	118164	118164	115003	118164

Table B.19.:

Intermediation, Opacity and Fragility, Intermediation Measured by the LT-Gap of Deep and Schaefer (2004), Opacity Based on $OLNJLY$.

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is the LT-Gap of Deep and Schaefer (2004). Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$OLNJLY$	0.0572***	0.588***	0.590***	0.439***	0.597***	0.583***
	(6.43)	(51.97)	(51.92)	(40.62)	(51.66)	(51.62)
$LAGTA$	-0.862***					
	(-136.73)					
$LEVRAG$		0.00425***				
		(12.42)				
NPL			0.233***			
			(5.69)			
$CREDRSK$				0.404***		
				(54.59)		
$ZIND_{MA(3)}$					-0.000138	
					(-1.00)	
$ZIND_{pool}$						-0.00347***
						(-16.70)

Continued on next page

Table B.19 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
BKSIZE	-0.0418***	-0.0218***	-0.0198***	-0.0359***	-0.0210***	-0.0212***
	(-22.09)	(-8.43)	(-7.71)	(-14.86)	(-7.71)	(-8.27)
CE	0.149***	0.246***	0.216***	0.229***	0.226***	0.258***
	(8.50)	(10.13)	(8.96)	(10.37)	(9.27)	(10.66)
ROA	1.159***	2.133***	2.076***	1.607***	1.838***	2.436***
	(20.66)	(25.80)	(24.12)	(21.89)	(22.24)	(28.37)
BKHHI	0.00376	-0.00887	-0.00856	-0.00976*	-0.00763	-0.00833
	(0.86)	(-1.46)	(-1.39)	(-1.71)	(-1.22)	(-1.37)
BKMSML	0.0104***	0.0135***	0.0137***	0.0148***	0.0121***	0.0127***
	(4.22)	(3.81)	(3.85)	(4.49)	(3.32)	(3.57)
BKPOP	0.00758***	0.0207***	0.0203***	0.0165***	0.0207***	0.0209***
	(6.99)	(13.24)	(12.86)	(11.43)	(12.87)	(13.41)
BKPDNS	-0.0000811	0.00621*	0.00476	0.00273	0.00490	0.00673*
	(-0.03)	(1.65)	(1.25)	(0.78)	(1.25)	(1.79)
BKICHG	0.0752***	0.0195***	0.0275***	0.0458***	0.0279***	0.0168***
	(15.46)	(3.08)	(4.32)	(7.52)	(4.39)	(2.65)
MBHC	-0.00353	0.00998***	0.0107***	0.00835**	0.0112***	0.00961**
	(-1.30)	(2.61)	(2.77)	(2.35)	(2.81)	(2.54)
OBHC	0.00551**	0.0178***	0.0199***	0.0183***	0.0208***	0.0168***
	(2.55)	(5.85)	(6.46)	(6.43)	(6.51)	(5.55)
MRG	0.0354	0.0295	0.0235	0.0163	0.0280	0.0303
	(1.12)	(0.66)	(0.52)	(0.36)	(0.59)	(0.67)
ACQ	-0.00188	-0.00216	-0.00293	-0.00303*	-0.00310*	-0.00192
	(-1.43)	(-1.17)	(-1.57)	(-1.80)	(-1.66)	(-1.05)
Constant	0.619***	-0.375***	-0.325***	-0.290***	-0.322***	-0.304***
	(20.87)	(-9.51)	(-8.17)	(-7.90)	(-7.88)	(-7.66)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.616	0.250	0.245	0.333	0.249	0.253
N	118164	118164	118164	118164	115003	118164

Table B.20.:

Intermediation, Opacity and Fragility, Intermediation Measured by the LT-Gap of Deep and Schaefer (2004), Opacity Based on $OPQFKN$.

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is the LT-Gap of Deep and Schaefer (2004). Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
$OPQFKN$	-0.156***	0.255***	0.0958**	-0.117***	0.118**	0.294***
	(-5.33)	(5.47)	(2.08)	(-2.89)	(2.52)	(6.40)
$LAGTA$	-0.882***					
	(-161.70)					
$LEVRAG$		0.00530***				
		(13.97)				
NPL			0.346***			
			(7.92)			
$CREDRSK$				0.496***		
				(64.18)		
$ZIND_{MA(3)}$					-0.000170	
					(-1.10)	
$ZIND_{pool}$						-0.00445***
						(-19.02)

Continued on next page

Table B.20 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
BKSIZE	-0.0427***	-0.0369***	-0.0339***	-0.0485***	-0.0351***	-0.0362***
	(-22.68)	(-13.44)	(-12.48)	(-19.55)	(-12.10)	(-13.36)
CE	0.152***	0.213***	0.183***	0.218***	0.192***	0.229***
	(8.64)	(8.40)	(7.25)	(9.64)	(7.50)	(9.03)
ROA	1.106***	2.583***	2.495***	1.700***	2.187***	2.989***
	(19.67)	(29.33)	(27.23)	(22.65)	(25.05)	(32.54)
BKHHI	0.00444	-0.00804	-0.00725	-0.00885	-0.00712	-0.00743
	(1.01)	(-1.24)	(-1.10)	(-1.49)	(-1.06)	(-1.14)
BKMSML	0.0106***	0.0158***	0.0163***	0.0167***	0.0143***	0.0147***
	(4.26)	(4.21)	(4.30)	(4.91)	(3.70)	(3.93)
BKPOP	0.00738***	0.0196***	0.0193***	0.0150***	0.0197***	0.0198***
	(6.71)	(11.38)	(11.06)	(9.85)	(11.08)	(11.59)
BKPDNS	-0.000275	0.00231	0.000636	-0.000277	0.00106	0.00301
	(-0.10)	(0.58)	(0.16)	(-0.08)	(0.25)	(0.75)
BKICHG	0.0757***	0.0193***	0.0293***	0.0502***	0.0286***	0.0157**
	(15.55)	(2.77)	(4.20)	(7.75)	(4.09)	(2.27)
MBHC	-0.00189	0.0128***	0.0152***	0.0128***	0.0159***	0.0119***
	(-0.69)	(3.10)	(3.64)	(3.43)	(3.67)	(2.91)
OBHC	0.00599***	0.0232***	0.0260***	0.0226***	0.0273***	0.0216***
	(2.76)	(7.09)	(7.87)	(7.62)	(7.93)	(6.69)
MRG	0.0374	0.0293	0.0235	0.0166	0.0289	0.0300
	(1.20)	(0.80)	(0.62)	(0.43)	(0.72)	(0.83)
ACQ	-0.00165	-0.00443**	-0.00503**	-0.00410**	-0.00533***	-0.00416**
	(-1.26)	(-2.27)	(-2.54)	(-2.38)	(-2.67)	(-2.15)
Constant	0.656***	-0.0382	0.0158	-0.0592	0.0205	0.0507
	(22.60)	(-0.95)	(0.39)	(-1.60)	(0.49)	(1.25)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.615	0.140	0.134	0.276	0.134	0.146
N	118164	118164	118164	118164	115003	118164

B.2. Robustness Checks

This section discusses several checks on the robustness of the results. First, it investigates whether results are affected by using the $CATNONFAT$ measure of Berger and Bouwman (2009) as the basis for intermediation quality. This is done in Section B.2.1. Second, this section investigates the impact that winsorization has on results. Specifically, Section B.2.2 considers the case where the variables of interest are winsorized at 2% and 98% instead of 1% and 99%. It finds strong support for the main findings. Moreover, related literature suggests that both OLS and truncated regression may be appropriate estimation methods in the context of efficiency scores. Hence Sections B.2.3 and B.2.4 investigate the impact of the estimation method choice on the results. Finally, Section B.2.5 also considers whether results change when the sample is split by bank size.

B.2.1. $CATNONFAT$ Underlies Intermediation Quality

The first check on the robustness of the results is to rerun the main analysis using the $CATNONFAT$ measure of liquidity creation (Berger and Bouwman, 2009) to parametrize the proxy of intermediation quality. Table B.21 reports results for the distributional properties of intermediation quality calculated on the basis of this measure. I find that the overall level of intermediation quality reported in the sample is about 20% greater than in the baseline case. This is not surprising given that $CATFAT$ includes off-balance-sheet items. Thus, while the inputs and outputs used in the frontier analysis remain the same, the $CATFAT$ measure assumes that banks are able to produce a greater level of liquidity. Also the dispersion of the intensity with which banks use off-balance-sheet items is likely to be large, with large banks being heavy users and small banks more reliant on traditional assets and liabilities. This extra variation in the dependent variable of the efficiency analysis also leads to a lower average level of productivity of some banks relative to the most efficient ones and hence lower minima.

In addition, Table B.22 reports correlations between the intermediation quality, opacity and fragility variables. In the main analysis, the intermediation quality measures were positively and negatively correlated with the opacity variables equally frequently. Similarly, if intermediation quality is based on $CATNONFAT$ and SFA, $OLNJLY$ and $OPQFKN$ are positively associated while $OOAJLY$ is negatively associated with intermediation quality. For IQ^{CNF}_{GFA}, $OOAJLY$ is significantly negatively related while $OLNJLY$ and $OPQFKN$ are significantly positively related with intermediation quality. Both intermediation quality parametrizations are positively (negatively) related to

Statistic	IQ^{CNF}_{SFA}	IQ^{CNF}_{GFA}
mean	0.7068	0.8468
median	0.7329	0.8636
min	0.0001	-0.4997
max	0.9840	1.0000
std	0.1428	0.0678
skewness	-1.7910	-5.6556

Table B.21.:
Summary Statistics of Intermediation Quality.
Distributional properties computed on a yearly basis and then averaged across years. SFA indicates stochastic frontier analysis, GFA indicates generalized frontier analysis and CNF indicates $CATNONFAT$ as specified in Berger and Bouwman (2009).

$CREDRSK$ ($LAGTA$, $ZIND_{MA(3)}$) but differ in their associations with the remaining fragility variables. This is similar to the main analysis and confirms the need for a multivariate analysis.

The second step is to investigate the association that holds between intermediation quality and liquidity creation in the absolute sense, both based on $CATNONFAT$. Results, reported in Table B.23, are extremely similar to the main analysis. The only difference is that the previously insignificant coefficient on $BKICHG$ gains significance while retaining its original sign. Moreover, SFA and GFA now agree on the association between intermediation quality and cost efficiency. It appears plausible that less affluent markets contribute to credit growth and thus absolute liquidity creation. Overall, as in the baseline case, higher liquidity creation is positively associated with larger, more cost efficient (CE) and profitable (ROA) banks that are holding companies and active in more populated markets ($BKPOP$) where large banks prefer to operate ($BKMSML$). More importantly, the association between the measures of intermediation quality and liquidity creation in the absolute is still significantly positive (IQ^{CNF}_{SFA}, IQ^{CNF}_{GFA}).

Third, Table B.24 considers the drivers of intermediation quality. Specifically, it runs the following regression.

$$\begin{aligned} IQ^{CNF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_i. \end{aligned} \tag{B.2}$$

Here $IQ^{CNF}_{m,i,t}$ stands for intermediation quality, based on $CATNONFAT$ with $m \in \{SFA, GFA\}$. All other variables are as defined in the main analysis. As found previously, bank size is negative, while return on assets is positive for intermediation quality.

Table B.22.:
Correlations of Opacity, Fragility and Intermediation Quality.
Pearson correlation coefficients between opacity, fragility and intermediation quality variables. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. $LAGTA$ represents liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. IQ_{SFA}^{CNF} (IQ_{GFA}^{CNF}) stands for intermediation quality parametrized using SFA (GFA) and Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation.

Parameter	IQ_{SFA}^{CNF}	IQ_{GFA}^{CNF}
IQ_{GFA}^{CNF}	0.3070***	1.0000
$OOAJLY$	-0.1310***	-0.2450***
$OLNJLY$	0.0923***	0.1070***
$OPQFKN$	0.0549***	-0.0288***
$LAGTA$	-0.1640***	-0.1080***
$LEVRAG$	0.0060**	-0.0515***
NPL	0.1350***	-0.0195***
$CREDRSK$	0.1680***	0.2230***
$ZIND_{MA(3)}$	-0.0157***	-0.0152***
$ZIND_{pool}$	-0.2550***	0.1060***

Parameter	(1)	(2)
IQ_{SFA}^{CNF}	0.288***	
	(52.83)	
IQ_{GFA}^{CNF}		0.164***
		(28.36)
$BKSIZE$	0.0185***	0.0144***
	(9.66)	(7.16)
CE	0.428***	0.0675***
	(22.54)	(3.61)
ROA	0.652***	0.960***
	(11.04)	(14.91)
$BKHHI$	0.00166	0.00105
	(0.37)	(0.21)
$BKMSML$	0.0181***	0.00594**
	(6.91)	(2.02)
$BKPOP$	0.0131***	0.0151***
	(10.57)	(10.87)
$BKPDNS$	0.00142	0.00367
	(0.52)	(1.21)
$BKICHG$	-0.0185***	-0.0270***
	(-3.73)	(-4.97)
$MBHC$	0.0175***	0.0291***
	(5.97)	(8.98)
$OBHC$	0.0178***	0.0242***
	(7.89)	(9.47)
MRG	0.0129	-0.00338
	(0.45)	(-0.11)
ACQ	-0.00104	-0.00160
	(-0.74)	(-1.05)
Constant	-0.767***	-0.371***
	(-24.87)	(-12.03)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.436	0.337
N	118164	118164

Table B.23.:
Liquidity Creation and Intermediation Quality.
Coefficients from regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation scaled by gross total assets. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Monetary values are in 2005 US Dollars. IQ_{SFA}^{CNF} (IQ_{GFA}^{CNF}) stands for intermediation quality parametrized using SFA (GFA) and the $CATNONFAT$ measure of liquidity creation from Berger and Bouwman (2009). Variables are winsorized at the 0.01 and 0.99 percentiles.

Furthermore, the table indicates that CE has a negative influence on intermediation quality just as in the baseline analysis. Intermediation quality is also lower in more concentrated markets ($BKHHI$) with stronger competitor presence ($BKMSML$). Again, as in the baseline case, holding companies that operate in affluent markets generally exhibit higher intermediation quality, especially if they have made recent acquisitions ($OBHC$, $MBHC$, $BKICHG$, ACQ). As in the main analysis, most of the relations between the explanatory variables and intermediation quality (with the exception of $BKHHI$) are confirmed by GFA in Specification 2.

Fourth, I turn to the investigation of the relation between intermediation quality and opacity. This is the first step required to disentangle the A1/A2 hypotheses from A3. More concretely, I run a Tobit regression of the form

$$\begin{aligned} IQ_{m,i,t}^{CNF} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,j,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_i, \end{aligned} \tag{B.3}$$

where $OP_{i,j,t}$ is the jth of the three opacity proxies. The findings are reported in Table B.25. The control variables exhibit identical signs and significances as in the analysis of the drivers of intermediation quality. More importantly, the opacity controls, $OLNJLY$ and $OPQFKN$ exhibit significant and positive associations with intermediation quality throughout for both IQ_{SFA}^{CNF} and IQ_{GFA}^{CNF}. As in the baseline case, $OOAJLY$ is insignificant. This finding reaffirms the results and conclusions obtained in the main analysis, namely that it is safe to reject both the null of no importance of opacity as well as the alternative A3, which embodies the "Opacity-Ownership Hypothesis".

Parameter	(1)	(2)
$BKSIZE$	-0.0555***	-0.0354***
	(-51.42)	(-67.42)
CE	-0.983***	-0.275***
	(-30.46)	(-24.93)
ROA	1.336***	-0.00839
	(14.44)	(-0.25)
$BKHHI$	-0.0172**	0.0109***
	(-2.43)	(5.73)
$BKMSML$	-0.000869	-0.000221
	(-0.20)	(-0.15)
$BKPOP$	0.00148**	0.00357***
	(2.11)	(15.29)
$BKPDNS$	-0.0102***	-0.00135***
	(-10.02)	(-4.28)
$BKICHG$	0.107***	0.0147***
	(10.15)	(4.48)
$MBHC$	0.0581***	0.0116***
	(19.14)	(11.51)
$OBHC$	0.0359***	0.0102***
	(13.78)	(12.83)
MRG	0.0277	0.0422
	(0.43)	(1.57)
ACQ	0.00884***	0.00334***
	(3.99)	(4.29)
Constant	2.224***	1.470***
	(62.13)	(105.47)
Time FE	Yes	Yes
N	118164	118164

Table B.24.:
Drivers of Intermediation Quality, Intermediation Quality Based on $CATNONFAT$.
Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Specification 1 is based on SFA, Specification 2 is based on GFA.

Table B.25.:
Intermediation Quality and Opacity, Intermediation Quality Based on $CATNONFAT$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATNONFAT$ measure of Berger and Bouwman (2009). Specifications 1-3 use SFA and 4-6 use GFA to obtain intermediation quality.

Parameter	(1)	(2)	(3)	(1)	(2)	(3)
$OOAJLY$	-0.0228			0.00787		
	(-0.55)			(0.44)		
$OLNJLY$		0.0954***			0.0157***	
		(10.28)			(4.83)	
$OPQFKN$			0.676***			0.235***
			(14.76)			(14.94)
$BKSIZE$	-0.0552***	-0.0548***	-0.0575***	-0.0355***	-0.0353***	-0.0361***
	(-48.97)	(-50.34)	(-52.60)	(-66.47)	(-67.09)	(-68.34)
CE	-0.981***	-0.996***	-0.995***	-0.276***	-0.277***	-0.279***
	(-30.05)	(-30.71)	(-30.82)	(-24.52)	(-24.96)	(-25.26)
ROA	1.316***	1.296***	1.682***	-0.00153	-0.0149	0.112***
	(13.40)	(13.96)	(17.59)	(-0.04)	(-0.44)	(3.18)
$BKHHI$	-0.0171**	-0.0153**	-0.0192***	0.0109***	0.0112***	0.0102***
	(-2.42)	(-2.19)	(-2.73)	(5.74)	(5.90)	(5.38)
$BKMSML$	-0.000780	0.000791	-0.00261	-0.000252	0.0000521	-0.000826
	(-0.18)	(0.18)	(-0.60)	(-0.17)	(0.04)	(-0.57)
$BKPOP$	0.00147**	0.00252***	0.00169**	0.00357***	0.00374***	0.00364***
	(2.10)	(3.54)	(2.43)	(15.27)	(15.73)	(15.67)
$BKPDNS$	-0.0102***	-0.00845***	-0.00988***	-0.00135***	-0.00106***	-0.00123***
	(-10.02)	(-8.19)	(-9.75)	(-4.26)	(-3.30)	(-3.92)
$BKICHG$	0.108***	0.105***	0.103***	0.0147***	0.0144***	0.0132***
	(10.20)	(10.00)	(9.85)	(4.48)	(4.39)	(4.06)
$MBHC$	0.0584***	0.0542***	0.0528***	0.0115***	0.0110***	0.00976***
	(19.04)	(18.17)	(17.45)	(11.30)	(11.04)	(9.73)
$OBHC$	0.0360***	0.0330***	0.0327***	0.0102***	0.00977***	0.00914***
	(13.76)	(12.92)	(12.66)	(12.72)	(12.33)	(11.55)
MRG	0.0283	0.0246	0.0178	0.0420	0.0417	0.0388
	(0.44)	(0.37)	(0.28)	(1.57)	(1.58)	(1.40)

Continued on next page

Table B.25 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(1)	(2)	(3)
ACQ	0.00892***	0.00938***	0.00589***	0.00331***	0.00342***	0.00231***
	(4.01)	(4.24)	(2.67)	(4.22)	(4.40)	(2.97)
Constant	2.221***	2.190***	2.227***	1.471***	1.464***	1.471***
	(61.06)	(60.19)	(62.21)	(104.04)	(104.86)	(105.81)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	118164	118164

The next step in the analysis requires one to disentangle A1 and A2. This is accomplished by way of a Tobit regression such as

$$\begin{aligned} IQ^{CNF}_{m,i,t} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\ &+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\ &+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \delta FRAG_{i,k,t} + \sum_{t=1}^{17} \theta_t d_t + \epsilon_i, \end{aligned} \tag{B.4}$$

where $FRAG_{i,k,t}$ is the kth of the six fragility proxies. Table B.26 reports the corresponding results. The results document that better intermediation quality is associated with greater fragility. Specifically, better intermediaries have higher leverage ($LEVRAG$), hold fewer liquid assets ($LAGTA$) and have lower quality loan portfolios (NPL). They have smaller Z-Scores ($ZIND_{MA(3)}, ZIND_{pool}$) as well as more risk weighted assets ($CREDRSK$). Both the SFA and GFA specifications support these findings. These results confirm that fragility is positively associated with the quality of intermediation and suggest that the acceptance of A2 in favor of A1 in the main analysis is warranted.

Table B.26.: Intermediation Quality and Fragility, Intermediation Quality Based on $CATNONFAT$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of SFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Intermediation quality is based on the $CATNONFAT$ measure of Berger and Bouwman (2009)and SFA in Specifications 1-6 and uses GFA in Specifications 7-12.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$LAGTA$	-0.239***						-0.0773***					
	(-29.53)						(-35.30)					
$LEVRAG$		0.00486***						0.00195***				
		(12.66)						(17.17)				
NPL			0.151***						0.113***			
			(3.01)						(5.97)			
$CREDRSK$				0.323***						0.0991***		
				(35.10)						(36.62)		
$ZIND_{MA(3)}$					-0.00160***						-0.000547***	
					(-7.69)						(-7.25)	
$ZIND_{pool}$						-0.00359***						-0.00107***
						(-13.55)						(-16.31)
$BKSIZE$	-0.0583***	-0.0571***	-0.0555***	-0.0595***	-0.0551***	-0.0570***	-0.0363***	-0.0360***	-0.0354***	-0.0366***	-0.0351***	-0.0358***
	(-54.27)	(-52.15)	(-51.44)	(-54.76)	(-50.41)	(-52.14)	(-70.70)	(-68.54)	(-67.39)	(-72.33)	(-66.51)	(-68.31)
CE	-0.965***	-0.950***	-0.982***	-0.966***	-0.981***	-0.937***	-0.269***	-0.262***	-0.274***	-0.270***	-0.272***	-0.262***
	(-31.68)	(-29.32)	(-30.42)	(-31.47)	(-30.30)	(-28.87)	(-25.70)	(-23.72)	(-24.88)	(-25.69)	(-24.65)	(-23.64)
ROA	1.506***	1.714***	1.427***	1.467***	1.436***	2.100***	0.0467	0.144***	0.0598*	0.0319	-0.0192	0.219***
	(17.13)	(18.69)	(13.81)	(16.74)	(14.95)	(21.94)	(1.42)	(4.30)	(1.65)	(0.97)	(-0.55)	(6.33)
$BKHHI$	-0.0119*	-0.0160**	-0.0180**	-0.0140**	-0.0186***	-0.0158**	0.0126***	0.0114***	0.0103***	0.0119***	0.0106***	0.0113***
	(-1.84)	(-2.29)	(-2.54)	(-2.16)	(-2.59)	(-2.26)	(7.09)	(6.08)	(5.43)	(6.66)	(5.52)	(6.05)
$BKMSML$	-0.0117***	-0.000858	-0.000533	-0.00528	-0.00108	-0.00130	-0.00371***	-0.000217	0.0000297	-0.00158	-0.000285	-0.000350
	(-2.86)	(-0.20)	(-0.12)	(-1.32)	(-0.24)	(-0.30)	(-2.67)	(-0.15)	(0.02)	(-1.15)	(-0.19)	(-0.24)
$BKPOP$	0.00116*	0.000992	0.00143**	0.000703	0.00145**	0.000977	0.00347***	0.00337***	0.00353***	0.00333***	0.00358***	0.00342***
	(1.78)	(1.44)	(2.05)	(1.10)	(2.05)	(1.42)	(15.63)	(14.67)	(15.15)	(15.26)	(15.08)	(14.85)
$BKPDNS$	-0.0112***	-0.00995***	-0.0103***	-0.00867***	-0.01000***	-0.0100***	-0.00167***	-0.00124***	-0.00137***	-0.000872***	-0.00131***	-0.00129***
	(-11.67)	(-9.85)	(-10.04)	(-9.15)	(-9.69)	(-9.98)	(-5.60)	(-4.00)	(-4.34)	(-2.96)	(-4.12)	(-4.18)
$BKICHG$	0.119***	0.0952***	0.110***	0.115***	0.107***	0.0915***	0.0187***	0.00988***	0.0167***	0.0170***	0.0141***	0.0100***
	(11.85)	(9.13)	(10.39)	(11.30)	(10.14)	(8.80)	(5.83)	(3.03)	(5.03)	(5.30)	(4.28)	(3.07)
$MBHC$	0.0480***	0.0512***	0.0581***	0.0477***	0.0576***	0.0493***	0.00835***	0.00883***	0.0116***	0.00840***	0.0113***	0.00899***
	(16.90)	(17.29)	(19.15)	(17.10)	(18.59)	(16.73)	(8.62)	(8.88)	(11.53)	(8.92)	(11.04)	(9.03)
$OBHC$	0.0297***	0.0303***	0.0358***	0.0286***	0.0358***	0.0285***	0.00825***	0.00801***	0.0102***	0.00801***	0.0100***	0.00805***
	(12.37)	(11.91)	(13.77)	(12.16)	(13.41)	(11.30)	(10.83)	(10.25)	(12.79)	(10.80)	(12.35)	(10.30)
MRG	0.0188	0.0346	0.0278	0.00539	0.0257	0.0348	0.0393	0.0450	0.0423	0.0353	0.0412	0.0443
	(0.29)	(0.53)	(0.43)	(0.08)	(0.39)	(0.52)	(1.46)	(1.64)	(1.57)	(1.43)	(1.54)	(1.63)
ACQ	0.00591***	0.0102***	0.00891***	0.00626***	0.00852***	0.0105***	0.00239***	0.00389***	0.00339***	0.00254***	0.00310***	0.00382***

Continued on next page

Table B.26 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(2.75)	(4.61)	(4.01)	(2.97)	(3.84)	(4.72)	(3.17)	(5.03)	(4.35)	(3.42)	(3.97)	(4.93)
Constant	2.341***	2.172***	2.221***	2.077***	2.218***	2.261***	1.508***	1.449***	1.467***	1.425***	1.465***	1.481***
	(68.96)	(60.05)	(62.03)	(59.66)	(61.74)	(63.66)	(111.66)	(103.50)	(105.47)	(108.79)	(105.34)	(107.12)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

Finally, to conclude the investigation, I run the regressions including both opacity and fragility together. Results can be found in Tables B.27-B.29. The specification is as follows

$$
\begin{aligned}
IQ_{m,i}^{CNF} = \alpha &+ \beta_1 BKSIZE_{i,t} + \beta_2 CE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 BKHHI_{i,t} + \beta_5 BKMSML_{i,t} \\
&+ \beta_6 BKPOP_{i,t} + \beta_7 BKPDNS_{i,t} + \beta_8 BKICHG_{i,t} + \beta_9 MBHC_{i,t} \\
&+ \beta_{10} OBHC_{i,t} + \beta_{11} MRG_{i,t} + \beta_{12} ACQ_{i,t} + \gamma OP_{i,j,t} + \delta FRAG_{i,k,t} \\
&+ \sum_{t=1}^{17} \theta_t d_t + \epsilon_i.
\end{aligned}
\tag{B.5}
$$

As these results confirm, the positive association between fragility and intermediation quality holds irrespective of whether opacity is included in the specification or not. Specifically, in the case of $OOAJLY$, the variable remains insignificant, while $OLNJLY$ retains its sign and significance in most cases. Exceptions are the regressions where $LAGTA$ and $CREDRSK$ proxy for fragility. This change of sign indicates that $OLNJLY$ contains information on some dimension of fragility, in particular to the extent that it is related to risk weighted assets. This is plausible given that $OLNJLY$ is constructed on the basis of other loans. However, the remaining conclusions are unchanged. Finally, $OPQFKN$ remains highly significant and positive. Thus using the $CATNONFAT$ measure as the basis for the intermediation quality proxy does not change the results and leads to the acceptance of the "Opacity-Fragility Hypothesis".

Table B.27.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATNONFAT$, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of GFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Liquidity creation is based on the $CATNONFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OOAJLY$	0.00100	-0.00240	-0.0257	-0.0827**	-0.0166	0.00501	0.0156	0.0161	0.00576	-0.0105	0.00674	0.0162
	(0.03)	(-0.06)	(-0.62)	(-2.10)	(-0.40)	(0.12)	(0.92)	(0.88)	(0.32)	(-0.61)	(0.37)	(0.89)
$LAGTA$	-0.239***						-0.0774***					
	(-29.56)						(-35.57)					
$LEVRAG$		0.00486***						0.00197***				
		(12.59)						(17.16)				
NPL			0.154***						0.112***			
			(3.07)						(5.88)			
$CREDRSK$				0.324***						0.0993***		
				(35.34)						(36.42)		
$ZIND_{MA(3)}$					-0.00161***						-0.000542***	
					(-7.78)						(-7.20)	
$ZIND_{pool}$						-0.00359***						-0.00108***
						(-13.51)						(-16.35)
$BKSIZE$	-0.0583***	-0.0570***	-0.0552***	-0.0586***	-0.0549***	-0.0571***	-0.0365***	-0.0362***	-0.0354***	-0.0365***	-0.0352***	-0.0360***
	(-51.64)	(-49.71)	(-48.99)	(-52.26)	(-48.12)	(-49.81)	(-70.06)	(-67.78)	(-66.37)	(-71.11)	(-65.54)	(-67.54)
CE	-0.965***	-0.950***	-0.980***	-0.960***	-0.980***	-0.938***	-0.271***	-0.263***	-0.275***	-0.269***	-0.272***	-0.263***
	(-31.24)	(-28.99)	(-30.00)	(-30.95)	(-29.92)	(-28.57)	(-25.29)	(-23.42)	(-24.45)	(-25.13)	(-24.22)	(-23.34)
ROA	1.507***	1.712***	1.407***	1.396***	1.421***	2.105***	0.0604*	0.159***	0.0644*	0.0228	-0.0133	0.235***
	(16.12)	(17.36)	(13.09)	(14.87)	(13.91)	(20.46)	(1.70)	(4.31)	(1.68)	(0.64)	(-0.35)	(6.17)
$BKHHI$	-0.0119*	-0.0160**	-0.0179**	-0.0135**	-0.0185***	-0.0158**	0.0125***	0.0113***	0.0103***	0.0120***	0.0105***	0.0112***
	(-1.84)	(-2.29)	(-2.53)	(-2.09)	(-2.59)	(-2.27)	(7.06)	(6.05)	(5.44)	(6.75)	(5.53)	(6.02)
$BKMSML$	-0.0117***	-0.000848	-0.000426	-0.00498	-0.00102	-0.00132	-0.00378***	-0.000279	0.00000575	-0.00154	-0.000311	-0.000414
	(-2.86)	(-0.20)	(-0.10)	(-1.24)	(-0.23)	(-0.31)	(-2.72)	(-0.19)	(0.00)	(-1.12)	(-0.21)	(-0.29)
$BKPOP$	0.00116*	0.000992	0.00142**	0.000688	0.00145**	0.000977	0.00347***	0.00338***	0.00354***	0.00333***	0.00358***	0.00342***
	(1.77)	(1.44)	(2.04)	(1.08)	(2.04)	(1.42)	(15.61)	(14.67)	(15.13)	(15.23)	(15.07)	(14.84)
$BKPDNS$	-0.0112***	-0.00995***	-0.0103***	-0.00870***	-0.0100***	-0.0100***	-0.00166***	-0.00123***	-0.00137***	-0.000876***	-0.00130***	-0.00129***
	(-11.66)	(-9.84)	(-10.05)	(-9.20)	(-9.69)	(-9.96)	(-5.56)	(-3.95)	(-4.32)	(-2.97)	(-4.10)	(-4.13)
$BKICHG$	0.119***	0.0953***	0.110***	0.115***	0.107***	0.0915***	0.0185***	0.00970***	0.0166***	0.0171***	0.0140***	0.00985***
	(11.88)	(9.16)	(10.44)	(11.42)	(10.18)	(8.82)	(5.81)	(2.99)	(5.03)	(5.35)	(4.27)	(3.03)
$MBHC$	0.0480***	0.0512***	0.0584***	0.0485***	0.0578***	0.0492***	0.00819***	0.00864***	0.0116***	0.00851***	0.0112***	0.00880***

Continued on next page

Table B.27 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(16.79)	(17.07)	(19.06)	(17.26)	(18.48)	(16.50)	(8.41)	(8.54)	(11.34)	(8.95)	(10.86)	(8.69)
$OBHC$	0.0297***	0.0303***	0.0359***	0.0289***	0.0358***	0.0285***	0.00818***	0.00792***	0.0102***	0.00805***	0.01000***	0.00797***
	(12.32)	(11.84)	(13.76)	(12.24)	(13.39)	(11.22)	(10.70)	(10.05)	(12.69)	(10.81)	(12.25)	(10.10)
MRG	0.0188	0.0347	0.0286	0.00777	0.0262	0.0346	0.0389	0.0445*	0.0421	0.0356	0.0410	0.0438
	(0.29)	(0.53)	(0.44)	(0.11)	(0.40)	(0.52)	(1.46)	(1.65)	(1.57)	(1.43)	(1.54)	(1.64)
ACQ	0.00590***	0.0102***	0.00900***	0.00654***	0.00857***	0.0104***	0.00233***	0.00383***	0.00337***	0.00258***	0.00307***	0.00376***
	(2.74)	(4.61)	(4.04)	(3.09)	(3.85)	(4.71)	(3.08)	(4.93)	(4.29)	(3.44)	(3.92)	(4.84)
Constant	2.341***	2.171***	2.217***	2.064***	2.216***	2.261***	1.510***	1.451***	1.468***	1.423***	1.466***	1.483***
	(67.55)	(59.18)	(60.91)	(58.42)	(60.73)	(62.56)	(110.33)	(102.45)	(103.95)	(106.64)	(103.81)	(105.76)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

Table B.28.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATNONFAT$, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of GFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Liquidity creation is based on the $CATNONFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OLNJLY$	-0.0115	0.0879***	0.0947***	-0.0465***	0.0935***	0.0838***	-0.0208***	0.0126***	0.0149***	-0.0306***	0.0146***	0.0121***
	(-1.23)	(9.61)	(10.25)	(-5.09)	(9.98)	(9.20)	(-5.95)	(3.89)	(4.59)	(-9.22)	(4.48)	(3.74)
$LAGTA$	-0.242***						-0.0829***					
	(-28.48)						(-34.10)					
$LEVRAG$		0.00459***						0.00192***				
		(12.12)						(16.65)				
NPL			0.0945*						0.104***			
			(1.92)						(5.54)			
$CREDRSK$				0.341***						0.111***		
				(35.52)						(39.30)		
$ZIND_{MA(3)}$					-0.00140***						-0.000516***	
					(-6.90)						(-6.91)	

Continued on next page

Table B.28 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ZIND_{pool}$						-0.00338***						-0.00104***
						(-12.99)						(-15.59)
$BKSIZE$	-0.0584***	-0.0564***	-0.0548***	-0.0600***	-0.0544***	-0.0564***	-0.0365***	-0.0359***	-0.0353***	-0.0370***	-0.0350***	-0.0357***
	(-54.16)	(-51.15)	(-50.35)	(-55.14)	(-49.34)	(-51.17)	(-70.23)	(-68.15)	(-67.05)	(-72.27)	(-66.19)	(-67.91)
CE	-0.963***	-0.964***	-0.995***	-0.958***	-0.995***	-0.951***	-0.266***	-0.264***	-0.277***	-0.265***	-0.274***	-0.264***
	(-31.46)	(-29.62)	(-30.68)	(-31.29)	(-30.61)	(-29.17)	(-25.42)	(-23.73)	(-24.90)	(-25.44)	(-24.69)	(-23.63)
ROA	1.513***	1.656***	1.354***	1.494***	1.386***	2.022***	0.0593*	0.135***	0.0483	0.0496	-0.0269	0.208***
	(17.25)	(18.02)	(13.07)	(17.11)	(14.38)	(21.15)	(1.82)	(4.04)	(1.33)	(1.53)	(-0.76)	(5.97)
$BKHHI$	-0.0121*	-0.0143**	-0.0158**	-0.0148**	-0.0166**	-0.0142**	0.0123***	0.0116***	0.0107***	0.0114***	0.0109***	0.0116***
	(-1.86)	(-2.07)	(-2.26)	(-2.27)	(-2.35)	(-2.06)	(6.93)	(6.20)	(5.61)	(6.43)	(5.69)	(6.16)
$BKMSML$	-0.0120***	0.000670	0.000989	-0.00634	0.000540	0.000181	-0.00432***	0.00000158	0.000269	-0.00227*	-0.0000320	-0.000135
	(-2.94)	(0.16)	(0.23)	(-1.58)	(0.12)	(0.04)	(-3.12)	(0.00)	(0.18)	(-1.68)	(-0.02)	(-0.09)
$BKPOP$	0.00103	0.00199***	0.00249***	0.000147	0.00251***	0.00193***	0.00323***	0.00352***	0.00370***	0.00297***	0.00374***	0.00356***
	(1.53)	(2.82)	(3.49)	(0.22)	(3.46)	(2.74)	(14.17)	(14.97)	(15.57)	(13.35)	(15.47)	(15.11)
$BKPDNS$	-0.0114***	-0.00833***	-0.00848***	-0.00945***	-0.00826***	-0.00849***	-0.00208***	-0.00101***	-0.00109***	-0.00138***	-0.00104***	-0.00107***
	(-11.67)	(-8.15)	(-8.21)	(-9.85)	(-7.91)	(-8.34)	(-6.84)	(-3.19)	(-3.40)	(-4.67)	(-3.21)	(-3.39)
$BKICHG$	0.120***	0.0942***	0.107***	0.116***	0.105***	0.0908***	0.0193***	0.00973***	0.0162***	0.0179***	0.0138***	0.00993***
	(11.90)	(9.04)	(10.14)	(11.45)	(9.99)	(8.74)	(6.06)	(2.99)	(4.90)	(5.59)	(4.20)	(3.04)
$MBHC$	0.0484***	0.0480***	0.0543***	0.0490***	0.0538***	0.0464***	0.00897***	0.00837***	0.0110***	0.00926***	0.0107***	0.00856***
	(17.09)	(16.39)	(18.19)	(17.64)	(17.67)	(15.89)	(9.38)	(8.54)	(11.08)	(9.94)	(10.61)	(8.72)
$OBHC$	0.0300***	0.0280***	0.0330***	0.0296***	0.0330***	0.0264***	0.00873***	0.00767***	0.00975***	0.00866***	0.00959***	0.00775***
	(12.48)	(11.14)	(12.92)	(12.57)	(12.59)	(10.58)	(11.51)	(9.89)	(12.31)	(11.74)	(11.90)	(9.98)
MRG	0.0191	0.0314	0.0247	0.00562	0.0229	0.0317	0.0398	0.0445*	0.0418	0.0355	0.0408	0.0439
	(0.30)	(0.47)	(0.37)	(0.08)	(0.34)	(0.46)	(1.44)	(1.65)	(1.58)	(1.40)	(1.55)	(1.64)
ACQ	0.00580***	0.0106***	0.00942***	0.00585***	0.00907***	0.0108***	0.00220***	0.00395***	0.00347***	0.00227***	0.00318***	0.00387***
	(2.70)	(4.81)	(4.25)	(2.78)	(4.09)	(4.90)	(2.93)	(5.11)	(4.46)	(3.07)	(4.09)	(5.01)
Constant	2.347***	2.144***	2.189***	2.085***	2.186***	2.229***	1.518***	1.445***	1.462***	1.430***	1.460***	1.476***
	(69.08)	(58.40)	(60.15)	(60.26)	(59.80)	(61.83)	(111.39)	(103.10)	(104.86)	(109.61)	(104.68)	(106.51)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

Table B.29.: Intermediation Quality, Opacity and Fragility, Intermediation Quality Based on $CATNONFAT$, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. $BKSIZE$ stands for the log of gross total assets, ROA stands for return on assets, CE is cost efficiency parametrized by way of GFA. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was merged (acquired) within the last three years. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. $LAGTA$ stands for liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles. Liquidity creation is based on the $CATNONFAT$ measure of Berger and Bouwman (2009). In Specifications 1-6, intermediation quality is based on SFA, in Specifications 7-12 it is based on GFA.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OPQFKN$	0.489***	0.747***	0.674***	0.455***	0.693***	0.738***	0.175***	0.263***	0.233***	0.167***	0.235***	0.253***
	(11.38)	(16.20)	(14.74)	(10.44)	(14.74)	(16.12)	(11.61)	(16.97)	(14.85)	(11.08)	(14.58)	(16.42)
$LAGTA$	-0.232***						-0.0747***					
	(-28.72)						(-33.93)					
$LEVRAG$		0.00545***						0.00216***				
		(14.26)						(19.30)				
NPL			0.128***						0.105***			
			(2.58)						(5.59)			
$CREDRSK$				0.313***						0.0955***		
				(34.48)						(35.51)		
$ZIND_{MA(3)}$					-0.00136***						-0.000466***	
					(-6.74)						(-6.34)	
$ZIND_{pool}$						-0.00385***						-0.00116***
						(-14.78)						(-17.99)
$BKSIZE$	-0.0597***	-0.0595***	-0.0575***	-0.0607***	-0.0572***	-0.0593***	-0.0368***	-0.0369***	-0.0361***	-0.0371***	-0.0358***	-0.0366***
	(-55.00)	(-53.49)	(-52.64)	(-55.35)	(-51.63)	(-53.45)	(-71.31)	(-69.76)	(-68.31)	(-72.77)	(-67.43)	(-69.43)
CE	-0.974***	-0.959***	-0.994***	-0.974***	-0.993***	-0.947***	-0.273***	-0.265***	-0.279***	-0.273***	-0.276***	-0.265***
	(-31.86)	(-29.63)	(-30.78)	(-31.60)	(-30.66)	(-29.20)	(-25.90)	(-24.03)	(-25.21)	(-25.85)	(-24.98)	(-23.95)
ROA	1.751***	2.142***	1.759***	1.696***	1.789***	2.535***	0.134***	0.294***	0.175***	0.116***	0.101***	0.369***
	(19.33)	(22.31)	(16.50)	(18.66)	(17.99)	(25.31)	(3.94)	(8.46)	(4.64)	(3.39)	(2.75)	(10.24)
$BKHHI$	-0.0135**	-0.0181***	-0.0199***	-0.0155**	-0.0207***	-0.0178***	0.0121***	0.0107***	0.00967***	0.0114***	0.00987***	0.0106***
	(-2.09)	(-2.60)	(-2.83)	(-2.38)	(-2.91)	(-2.58)	(6.73)	(5.69)	(5.09)	(6.32)	(5.16)	(5.66)
$BKMSML$	-0.0126***	-0.00278	-0.00232	-0.00632	-0.00282	-0.00323	-0.00404***	-0.000893	-0.000588	-0.00196	-0.000873	-0.00101
	(-3.09)	(-0.65)	(-0.53)	(-1.57)	(-0.64)	(-0.76)	(-2.93)	(-0.63)	(-0.41)	(-1.44)	(-0.60)	(-0.71)
$BKPOP$	0.00133**	0.00117*	0.00165**	0.000872	0.00166**	0.00118*	0.00353***	0.00344***	0.00361***	0.00339***	0.00365***	0.00349***
	(2.03)	(1.71)	(2.37)	(1.36)	(2.34)	(1.72)	(15.89)	(15.02)	(15.53)	(15.53)	(15.43)	(15.21)
$BKPDNS$	-0.0109***	-0.00952***	-0.00990***	-0.00847***	-0.00965***	-0.00963***	-0.00157***	-0.00109***	-0.00125***	-0.000801***	-0.00119***	-0.00116***
	(-11.40)	(-9.50)	(-9.76)	(-8.96)	(-9.43)	(-9.65)	(-5.26)	(-3.54)	(-3.98)	(-2.72)	(-3.79)	(-3.76)
$BKICHG$	0.116***	0.0889***	0.105***	0.112***	0.103***	0.0856***	0.0174***	0.00766**	0.0150***	0.0158***	0.0128***	0.00800**
	(11.59)	(8.64)	(10.05)	(11.08)	(9.90)	(8.34)	(5.48)	(2.38)	(4.58)	(4.97)	(3.93)	(2.48)
$MBHC$	0.0445***	0.0444***	0.0528***	0.0444***	0.0524***	0.0428***	0.00708***	0.00645***	0.00977***	0.00719***	0.00948***	0.00675***

Continued on next page

Table B.29 – *Continued from previous page*

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(15.63)	(15.09)	(17.47)	(15.85)	(16.98)	(14.60)	(7.34)	(6.55)	(9.75)	(7.62)	(9.35)	(6.85)
$OBHC$	0.0276***	0.0261***	0.0326***	0.0267***	0.0326***	0.0245***	0.00749***	0.00653***	0.00910***	0.00731***	0.00896***	0.00667***
	(11.49)	(10.34)	(12.65)	(11.30)	(12.34)	(9.77)	(9.88)	(8.45)	(11.51)	(9.84)	(11.15)	(8.62)
MRG	0.0119	0.0245	0.0179	-0.000574	0.0158	0.0245	0.0369	0.0414	0.0389	0.0332	0.0378	0.0408
	(0.19)	(0.39)	(0.28)	(-0.01)	(0.25)	(0.38)	(1.34)	(1.47)	(1.40)	(1.31)	(1.37)	(1.46)
ACQ	0.00386*	0.00711***	0.00596***	0.00435**	0.00551**	0.00735***	0.00166**	0.00280***	0.00237***	0.00184**	0.00208***	0.00275***
	(1.81)	(3.25)	(2.70)	(2.07)	(2.49)	(3.36)	(2.20)	(3.63)	(3.03)	(2.47)	(2.66)	(3.57)
Constant	2.340***	2.169***	2.224***	2.083***	2.222***	2.267***	1.507***	1.448***	1.469***	1.427***	1.466***	1.483***
	(68.82)	(60.05)	(62.14)	(59.73)	(61.81)	(63.90)	(111.80)	(103.98)	(105.83)	(108.76)	(105.68)	(107.63)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118164	118164	118164	118164	115003	118164	118164	118164	118164	118164	115003	118164

.

B.2.2. Regressions with Data Winsorized at 2% and 98%

This section investigates whether and how results change if the data is winsorized at 2 and 98% instead of at 1 and 99%. This is so as to avoid outliers driving the results. Findings are similar when the winsorization is instead chosen at 5 and 95% and hence these additional results remain unreported.

The main analysis shows that for the parametrization of intermediation quality that uses SFA and $CATFAT$, both $OLNJLY$ and $OPQFKN$ are significantly positively associated with intermediation quality. In the case of GFA, $OPQFKN$ is also significantly positive, while $OLNJLY$ is significantly negative. $OOAJLY$ is insignificant in all cases. This last finding extends to the instance when intermediation quality is parametrized by way of $CATNONFAT$. However, the negative coefficient on $OLNJLY$ for GFA intermediation quality turns significantly positive in this case.

Consider in contrast the results reported in Panel A of Table B.30. While here the significantly negative coefficient on $OLNJLY$ when GFA and $CATFAT$ parametrize intermediation quality holds, $OOAJLY$ is now significantly positive throughout. This provides strong confirmation for the results found in the main analysis. This confirmation is further strengthened by the findings on fragility. These are almost completely unchanged. Only the coefficient on NPL loses significance in the case where $CATFAT$ and SFA parametrize intermediation quality (Panel B1). The results when $CATNONFAT$ is used to obtain the intermediation quality measure are qualitatively unaffected.

Finally, in the joint analysis of opacity and fragility, the main investigation shows that $OOAJLY$ is mostly insignificant, $OLNJLY$ mostly significantly positive except when using GFA to obtain intermediation quality, and $OPQFKN$ is significantly positively associated with intermediation quality throughout. Even stronger results obtain when $CATNONFAT$ is used to obtain intermediation quality but $OOAJLY$ remains insignificant.

In contrast, Table B.30 shows that in the case of $OLNJLY$, as previously, when GFA and $CATFAT$ define the intermediation quality measure, the coefficients are significantly negative (Panel C2). Also when $LAGTA$ and $CREDRSK$ parametrize fragility, $OLNJLY$ is significantly negative throughout (Panels C2, D2). However, it is significantly positive in the remainder of cases. Moreover, Panels C1 and D1 show that $OOAJLY$ is positively and significantly associated with intermediation quality throughout and that the same holds for $OPQFKN$ (Panels C3 and D3).

This additional analysis once again confirms the main findings and shows that previously insignificant results running counter to the main interpretation are at least partly driven by outliers.

Table B.30.: Intermediation Quality, Opacity and Fragility with Data Winsorized at 2 and 98%.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.02 and 0.98 percentiles.

	Panel A: Opacity											
	Panel A1: CATFAT						**Panel A2: CATNONFAT**					
	SFA			**GFA**			**SFA**			**GFA**		
	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
Opacity	0.280***	0.118***	0.813***	0.0644***	-0.0633***	0.112***	0.193***	0.0936***	0.671***	0.0652***	0.0152***	(16.84)
	(5.90)	(10.40)	(14.90)	(4.30)	(-20.15)	(7.64)	(4.65)	(10.61)	(15.43)	(4.38)	(5.33)	0.240***
	Panel B1: Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.310***	0.00520***	0.0933	0.443***	-0.00304***	-0.00359***	-0.0749***	0.00373***	-0.0233	0.0967***	-0.00125***	-0.00200***
	(-32.22)	(11.01)	(1.34)	(41.19)	(-8.21)	(-11.40)	(-37.86)	(34.58)	(-1.32)	(38.31)	(-10.00)	(-32.38)
	Panel B2: Fragility, CATNONFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.227***	0.00465***	0.130***	0.317***	-0.00261***	-0.00340***	-0.0739***	0.00190***	0.109***	0.0960***	-0.000857***	-0.00103***
	(-30.42)	(12.59)	(2.61)	(37.51)	(-8.61)	(-13.43)	(-39.08)	(18.32)	(6.08)	(40.99)	(-8.45)	(-17.29)
	Panel C1: Opacity ($OOAJLY$) and Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.235***	0.314***	0.278***	0.114**	0.299***	0.318***	0.0537***	0.0885***	0.0654***	0.0282**	0.0644***	0.0854***
	(5.35)	(6.52)	(5.84)	(2.58)	(6.19)	(6.61)	(3.74)	(5.95)	(4.35)	(1.98)	(4.26)	(5.78)
Fragility	-0.309***	0.00541***	0.0547	0.441***	-0.00274***	-0.00372***	-0.0746***	0.00379***	-0.0324*	0.0961***	-0.00119***	-0.00204***
	(-32.23)	(11.37)	(0.78)	(41.08)	(-7.54)	(-11.80)	(-37.41)	(35.03)	(-1.83)	(37.49)	(-9.56)	(-32.96)

Continued on next page

Table B.30 – *Continued from previous page*

	SFA						GFA					
Panel C2: Opacity ($OLNJLY$) and Fragility, CATFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0225**	0.109***	0.117***	-0.0814***	0.114***	0.106***	-0.109***	-0.0704***	-0.0634***	-0.125***	-0.0639***	-0.0712***
	(-2.09)	(9.81)	(10.44)	(-7.77)	(9.88)	(9.55)	(-33.47)	(-22.79)	(-20.21)	(-39.33)	(-20.12)	(-23.01)
Fragility	-0.316***	0.00483***	0.0211	0.475***	-0.00264***	-0.00331***	-0.104***	0.00398***	0.0156	0.146***	-0.00148***	-0.00219***
	(-31.93)	(10.44)	(0.31)	(43.42)	(-7.30)	(-10.77)	(-49.39)	(36.75)	(0.91)	(56.25)	(-11.85)	(-35.00)
Panel C3: Opacity ($OPQFKN$) and Fragility, CATFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.550***	0.879***	0.812***	0.489***	0.842***	0.861***	0.0472***	0.156***	0.113***	0.0402***	0.107***	0.138***
	(11.01)	(15.94)	(14.90)	(9.85)	(15.11)	(15.75)	(3.37)	(11.10)	(7.67)	(2.87)	(7.14)	(9.81)
Fragility	-0.301***	0.00578***	0.0618	0.432***	-0.00253***	-0.00383***	-0.0741***	0.00384***	-0.0277	0.0958***	-0.00119***	-0.00204***
	(-31.57)	(12.24)	(0.89)	(40.56)	(-7.00)	(-12.30)	(-36.98)	(35.79)	(-1.58)	(37.55)	(-9.54)	(-33.23)
Panel D1: Opacity ($OOAJLY$) and Fragility, CATNONFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.161***	0.224***	0.190***	0.0744*	0.202***	0.229***	0.0546***	0.0776***	0.0620***	0.0292**	0.0638***	0.0762***
	(4.09)	(5.33)	(4.56)	(1.87)	(4.78)	(5.46)	(3.89)	(5.18)	(4.16)	(2.07)	(4.23)	(5.11)
Fragility	-0.227***	0.00480***	0.104**	0.316***	-0.00240***	-0.00349***	-0.0736***	0.00195***	0.0999***	0.0954***	-0.000793***	-0.00107***
	(-30.33)	(12.96)	(2.08)	(37.38)	(-8.08)	(-13.85)	(-38.52)	(18.75)	(5.59)	(40.29)	(-7.92)	(-17.84)
Panel D2: Opacity ($OLNJLY$) and Fragility, CATNONFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.00825	0.0858***	0.0931***	-0.0469***	0.0913***	0.0821***	-0.0200***	0.0118***	0.0144***	-0.0300***	0.0140***	0.0115***
	(-0.92)	(9.87)	(10.59)	(-5.38)	(10.24)	(9.48)	(-6.56)	(4.19)	(5.06)	(-10.35)	(4.89)	(4.07)
Fragility	-0.229***	0.00436***	0.0732	0.336***	-0.00228***	-0.00318***	-0.0791***	0.00186***	0.0997***	0.108***	-0.000808***	-0.00100***
	(-29.06)	(11.98)	(1.48)	(37.94)	(-7.70)	(-12.78)	(-37.71)	(17.82)	(5.60)	(43.63)	(-8.04)	(-16.60)
Panel D3: Opacity ($OPQFKN$) and Fragility, CATNONFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.479***	0.729***	0.669***	0.440***	0.685***	0.716***	0.178***	0.264***	0.239***	0.171***	0.239***	0.254***
	(11.72)	(16.69)	(15.41)	(10.76)	(15.39)	(16.48)	(13.03)	(18.72)	(16.74)	(12.57)	(16.38)	(18.07)
Fragility	-0.220***	0.00513***	0.105**	0.307***	-0.00219***	-0.00360***	-0.0711***	0.00207***	0.0993***	0.0923***	-0.000714***	-0.00111***
	(-29.50)	(14.00)	(2.11)	(36.70)	(-7.42)	(-14.46)	(-37.36)	(20.37)	(5.60)	(39.51)	(-7.18)	(-18.85)

B.2.3. Analysis Using Fixed Effects Regression

This section reports results that obtain when, instead of Tobit regressions, estimations are carried out using a linear regression model as has been done for example by Pi and Timme (1993). Specifically, this section uses a regression including both time and bank fixed effects and clusters standard errors by bank.

Results reported in Table B.31 are very much in line with the main analysis. Thus Panel A reports findings on opacity. Results show that the initial finding of a positive relation between opacity and intermediation quality persists in the majority of cases and is particularly strong when $CATNONFAT$ is used to parametrize intermediation quality.

In addition, the signs and significances of the fragility proxies reported in Panel B1 and B2 are also mostly in line with the main findings. Thus, in Panel B1 only $LEVRAG$ and $ZIND_{MA(3)}$ lose their significance and $ZIND_{pool}$ switches sign when SFA is used to obtain intermediation quality and NPL loses significance when GFA is used for this purpose. All other variables maintain their sign and significance relative to the main analysis. In Panel B2, when $CATNONFAT$ is the basis for intermediation quality, results are even stronger. Here only NPL and $ZIND_{MA(3)}$ lose significance when SFA is used to obtain intermediation quality. Again, the remaining variables are as in the main analysis.

Finally, Panels C1 and D1 show that if fixed effects regressions are used for the purposes of estimation, $OOAJLY$, which is insignificant in the main analysis, becomes positive and significant. This specifically holds when intermediation quality is parametrized by SFA. It also holds when intermediation quality is parametrized by GFA and $CATNONFAT$. When intermediation quality is parametrized using $CATFAT$, $OOAJLY$ is positive and significant for the settings where fragility is proxied by $LEVRAG$ and $ZIND_{pool}$. Moreover, the findings on fragility are also robust. Thus only $LEVRAG$, $ZIND_{MA(3)}$ and $ZIND_{pool}$ lose significance when $CATFAT$ and SFA define intermediation quality. Only NPL loses significance in the GFA case. When $CATNONFAT$ is used to obtain intermediation quality, results are even stronger. Here only $ZIND_{MA(3)}$ and NPL become insignificant for SFA. While the evidence on $OLNJLY$ is mixed, the majority of coefficients is significantly positive, the exception being those in regressions also including $LAGTA$ and $CREDRSK$ when SFA is the basis for intermediation quality. Additionally, when GFA and $CATFAT$ are used to obtain the frontier all coefficients on $OLNJLY$ are significantly negative. However, this changes when $CATNONFAT$ is used to obtain intermediation quality. Here, with the exception of the case where $LAGTA$ proxies for fragility, all opacity coefficients are significantly positive. As can be seen from Panels C3 and D3, $OPQFKN$ is consistently positive and significant, with the exception of some insignificant coefficients in the case of GFA in Panel C3. Finally, the fragility results in Panels C2, C3, D2 and D3 are also very much in line with the main analysis.

Therefore, overall, the evidence strongly suggests that resorting to a linear regression analysis over a Tobit regression will leave the conclusions qualitatively unaffected.

Table B.31.: Intermediation Quality, Opacity and Fragility, Analysis Using Fixed Effects Regression.

Coefficients from linear regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: Opacity											
	Panel A1: CATFAT						**Panel A2: CATNONFAT**					
	SFA			**GFA**			**SFA**			**GFA**		
	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
Opacity	0.334***	0.0254**	0.659***	0.0232	-0.0829***	-0.0245	0.205***	0.0595***	0.590***	0.0803***	0.0243***	0.190***
	(9.42)	(2.16)	(14.07)	(1.30)	(-16.64)	(-1.26)	(6.06)	(6.26)	(14.49)	(5.80)	(6.58)	(12.00)
	Panel B1: Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.256***	-0.000221	0.180***	0.212***	0.000196	0.000591**	-0.0496***	0.00307***	0.00513	0.0602***	-0.000204**	-0.00110***
	(-27.31)	(-0.59)	(4.23)	(26.53)	(1.25)	(2.33)	(-15.24)	(19.98)	(0.31)	(19.07)	(-2.54)	(-11.41)
	Panel B2: Fragility, CATNONFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.215***	0.000673**	-0.0271	0.168***	0.000132	-0.00119***	-0.0651***	0.000750***	0.104***	0.0378***	-0.000107**	-0.0000492
	(-28.23)	(2.07)	(-0.75)	(24.28)	(0.97)	(-5.21)	(-25.39)	(6.06)	(7.08)	(16.25)	(-2.05)	(-0.67)
	Panel C1: Opacity ($OOAJLY$) and Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.367***	0.340***	0.331***	0.310***	0.351***	0.332***	0.0294*	0.0627***	0.0232	0.0161	0.0277	0.0484***
	(10.34)	(9.50)	(9.35)	(8.76)	(9.61)	(9.20)	(1.65)	(3.54)	(1.30)	(0.91)	(1.53)	(2.72)
Fragility	-0.260***	0.000464	0.158***	0.209***	0.000242	0.000128	-0.0499***	0.00319***	0.00356	0.0601***	-0.000200**	-0.00116***
	(-27.79)	(1.24)	(3.71)	(26.34)	(1.55)	(0.50)	(-15.39)	(20.86)	(0.21)	(19.01)	(-2.49)	(-12.11)

Continued on next page

Table B.31 – *Continued from previous page*

Panel C2: Opacity ($OLNJLY$) and Fragility, CATFAT

	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.166***	0.0256**	0.0241**	-0.0590***	0.0241**	0.0269**	-0.142***	-0.0855***	-0.0831***	-0.115***	-0.0837***	-0.0858***
	(-13.79)	(2.18)	(2.05)	(-5.13)	(2.00)	(2.29)	(-25.95)	(-17.15)	(-16.66)	(-22.80)	(-16.39)	(-17.21)
Fragility	-0.309***	-0.000244	0.176***	0.224***	0.000198	0.000620**	-0.0951***	0.00314***	0.0210	0.0838***	-0.000210***	-0.00119***
	(-30.16)	(-0.66)	(4.13)	(27.54)	(1.26)	(2.45)	(-26.60)	(20.71)	(1.27)	(25.92)	(-2.63)	(-12.51)

Panel C3: Opacity ($OPQFKN$) and Fragility, CATFAT

	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.587***	0.694***	0.659***	0.571***	0.696***	0.668***	-0.0388**	0.0721***	-0.0245	-0.0507***	-0.0251	0.0257
	(12.65)	(14.40)	(14.09)	(12.31)	(14.49)	(13.81)	(-1.99)	(3.77)	(-1.26)	(-2.61)	(-1.24)	(1.36)
Fragility	-0.251***	0.00119***	0.180***	0.204***	0.000271*	-0.000204	-0.0500***	0.00321***	0.00512	0.0609***	-0.000207**	-0.00113***
	(-26.91)	(3.11)	(4.26)	(25.72)	(1.74)	(-0.79)	(-15.20)	(20.82)	(0.31)	(19.11)	(-2.57)	(-11.86)

Panel D1: Opacity ($OOAJLY$) and Fragility, CATNONFAT

	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.232***	0.219***	0.206***	0.186***	0.214***	0.238***	0.0884***	0.0918***	0.0784***	0.0759***	0.0844***	0.0839***
	(6.93)	(6.41)	(6.07)	(5.46)	(6.07)	(6.91)	(6.46)	(6.52)	(5.67)	(5.49)	(6.03)	(5.95)
Fragility	-0.217***	0.00111***	-0.0411	0.166***	0.000160	-0.00152***	-0.0659***	0.000935***	0.0992***	0.0371***	-0.0000958*	-0.000166**
	(-28.63)	(3.43)	(-1.13)	(24.12)	(1.18)	(-6.65)	(-25.78)	(7.42)	(6.72)	(15.94)	(-1.84)	(-2.20)

Panel D2: Opacity ($OLNJLY$) and Fragility, CATNONFAT

	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0918***	0.0590***	0.0598***	-0.00404	0.0591***	0.0568***	-0.0200***	0.0237***	0.0235***	0.0109***	0.0244***	0.0242***
	(-9.04)	(6.21)	(6.29)	(-0.42)	(6.08)	(5.99)	(-4.79)	(6.41)	(6.37)	(2.86)	(6.51)	(6.54)
Fragility	-0.244***	0.000619*	-0.0385	0.169***	0.000136	-0.00113***	-0.0715***	0.000728***	0.1000***	0.0356***	-0.000105**	-0.0000234
	(-28.75)	(1.91)	(-1.06)	(23.37)	(1.01)	(-4.95)	(-24.10)	(5.87)	(6.76)	(14.69)	(-2.02)	(-0.32)

Panel D3: Opacity ($OPQFKN$) and Fragility, CATNONFAT

	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.530***	0.649***	0.590***	0.521***	0.620***	0.679***	0.172***	0.226***	0.190***	0.175***	0.196***	0.203***
	(13.00)	(15.88)	(14.49)	(12.79)	(14.78)	(16.61)	(10.89)	(14.28)	(12.02)	(11.10)	(12.13)	(12.84)
Fragility	-0.210***	0.00199***	-0.0269	0.160***	0.000198	-0.00200***	-0.0635***	0.00121***	0.105***	0.0354***	-0.0000857*	-0.000291***
	(-27.64)	(6.14)	(-0.75)	(23.36)	(1.47)	(-8.84)	(-24.67)	(9.73)	(7.14)	(15.23)	(-1.65)	(-3.92)

B.2.4. Analysis Using Truncated Regression

This robustness check re-estimates the analyses regarding opacity and fragility using truncated regression as argued by Simar and Wilson (2007). Specifically, Table B.32 reports results on opacity for both the $CATFAT$ and $CATNONFAT$ measures of liquidity creation and both SFA and GFA underlying intermediation quality.

Results in Panel A relate to opacity and are extremely similar to the main analysis not only in sign but also in the magnitude and significance of the coefficients. Specifically, $OOAJLY$ is mostly insignificant but positive. With the exception of the case where intermediation quality is parametrized by GFA and $CATFAT$, $OLNJLY$ is also positive and significant. Finally, $OPQFKN$ is consistently positive and significant. This suggests that the theoretical issues raised by Simar and Wilson (2007) are of only limited practical importance in the present analysis. The coefficients on the opacity proxies once again confirm that the majority of the evidence supports the conclusion that opacity is positively associated with intermediation quality.

Panels B1 and B2 report results for fragility alone. Here too, the main findings find confirmation. Specifically, $LAGTA$, $ZIND_{MA(3)}$ and $ZIND_{pool}$ are significantly negatively associated with intermediation quality. In addition, $LEVRAG$, NPL and $CREDRSK$ display a significantly positive relation. All of these point towards a positive association between fragility and intermediation quality. Thus, the results suggest that fragility is beneficial for intermediation quality.

Finally, Panels C1-C3 and D1-D3 include both opacity and fragility for the $CATFAT$ and $CATNONFAT$ measures respectively. Again, the main findings are confirmed in sign, magnitude and significance of the coefficients. Thus the previously insignificant $OOAJLY$ becomes positively significant in some cases when GFA is the efficiency parametrization method (Panel C1, D1). The corresponding fragility coefficients point in the same direction as in the main analysis. The majority of the coefficients on $OLNJLY$ are significantly positive (Panel C2, SFA; Panel D2). They tend to become negative either when $CREDRSK$ or $LAGTA$ measure fragility or when GFA and the $CATFAT$ liquidity creation measure are used to parametrize intermediation quality. The fragility results are qualitatively unaffected by the use of $OLNJLY$ as opacity proxy. Finally, when $OPQFKN$ proxies for opacity this variable is significantly positive throughout (Panels C3, D3). In addition, the fragility results are also very similar to the main analysis, with the exception of NPL which tends to lose significance when SFA parametrizes intermediation quality. These findings support the original conclusion, that both opacity and fragility are beneficial for intermediation quality.

Hence, overall, I conclude that the choice of Tobit regressions over truncated regressions has not materially affected the findings.

Table B.32.: Intermediation Quality, Opacity and Fragility, Analysis Using Truncated Regression.

Coefficients from truncated regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: Opacity											
	Panel A1: CATFAT						**Panel A2: CATNONFAT**					
	SFA			**GFA**			**SFA**			**GFA**		
	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
Opacity	-0.00701	0.125***	0.856***	0.0267	-0.0669***	0.0976***	0.0214	0.120***	0.837***	0.0120	0.0177***	0.248***
	(-0.15)	(10.14)	(14.81)	(1.40)	(-18.49)	(5.82)	(0.46)	(10.83)	(14.78)	(0.65)	(5.21)	(14.92)
	Panel B1: Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.337***	0.00573***	0.137*	0.467***	-0.00194***	-0.00400***	-0.0793***	0.00390***	-0.00615	0.102***	-0.000785***	-0.00207***
	(-31.07)	(11.20)	(1.94)	(38.56)	(-7.31)	(-11.72)	(-34.61)	(32.60)	(-0.32)	(35.17)	(-8.14)	(-30.90)
	Panel B2: Fragility, CATNONFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
Fragility	-0.276***	0.00590***	0.0145	0.380***	-0.00167***	-0.00424***	-0.0801***	0.00204***	0.123***	0.104***	-0.000562***	-0.00112***
	(-28.51)	(12.82)	(0.21)	(33.72)	(-7.56)	(-14.34)	(-35.05)	(17.22)	(6.23)	(36.03)	(-7.37)	(-16.44)
	Panel C1: Opacity ($OOAJLY$) and Fragility, CATFAT											
	SFA						**GFA**					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.0246	0.0166	-0.00960	-0.0951**	0.00612	0.0235	0.0351*	0.0432**	0.0269	0.00790	0.0312	0.0429**
	(0.59)	(0.36)	(-0.21)	(-2.29)	(0.13)	(0.51)	(1.92)	(2.26)	(1.41)	(0.44)	(1.64)	(2.25)
Fragility	-0.337***	0.00575***	0.139*	0.468***	-0.00194***	-0.00401***	-0.0795***	0.00394***	-0.00967	0.101***	-0.000763***	-0.00209***
	(-31.06)	(11.13)	(1.95)	(38.72)	(-7.35)	(-11.66)	(-35.03)	(32.59)	(-0.50)	(34.65)	(-7.94)	(-31.04)

Continued on next page

Table B.32 – *Continued from previous page*

	SFA						GFA					
Panel C2: Opacity ($OLNJLY$) and Fragility, CATFAT												
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0285**	0.116***	0.125***	-0.0847***	0.121***	0.112***	-0.115***	-0.0736***	-0.0671***	-0.131***	-0.0673***	-0.0746***
	(-2.47)	(9.59)	(10.15)	(-7.52)	(9.67)	(9.31)	(-30.26)	(-20.57)	(-18.60)	(-35.51)	(-18.37)	(-20.80)
Fragility	-0.344***	0.00536***	0.0648	0.500***	-0.00168***	-0.00372***	-0.110***	0.00413***	0.0338*	0.154***	-0.000927***	-0.00225***
	(-31.03)	(10.71)	(0.93)	(40.61)	(-6.53)	(-11.19)	(-44.97)	(34.40)	(1.81)	(51.19)	(-9.56)	(-33.00)
Panel C3: Opacity ($OPQFKN$) and Fragility, CATFAT												
	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.581***	0.937***	0.855***	0.524***	0.889***	0.922***	0.0340**	0.151***	0.0977***	0.0254	0.0941***	0.132***
	(11.20)	(16.04)	(14.81)	(10.07)	(15.02)	(15.93)	(2.12)	(9.44)	(5.83)	(1.59)	(5.50)	(8.27)
Fragility	-0.328***	0.00645***	0.111	0.455***	-0.00164***	-0.00432***	-0.0788***	0.00402***	-0.00935	0.101***	-0.000753***	-0.00212***
	(-30.54)	(12.56)	(1.59)	(38.09)	(-6.37)	(-12.75)	(-33.94)	(33.88)	(-0.49)	(34.62)	(-7.87)	(-31.85)
Panel D1: Opacity ($OOAJLY$) and Fragility, CATNONFAT												
	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.0564	0.0468	0.0212	-0.0424	0.0284	0.0561	0.0208	0.0206	0.00977	-0.00657	0.0107	0.0207
	(1.30)	(1.00)	(0.46)	(-0.98)	(0.61)	(1.20)	(1.19)	(1.10)	(0.53)	(-0.38)	(0.57)	(1.11)
Fragility	-0.276***	0.00594***	0.0116	0.380***	-0.00165***	-0.00427***	-0.0802***	0.00206***	0.122***	0.104***	-0.000554***	-0.00113***
	(-28.57)	(12.85)	(0.17)	(33.83)	(-7.52)	(-14.42)	(-35.33)	(17.24)	(6.11)	(35.85)	(-7.30)	(-16.51)
Panel D2: Opacity ($OLNJLY$) and Fragility, CATNONFAT												
	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.00341	0.111***	0.121***	-0.0444***	0.118***	0.106***	-0.0200***	0.0144***	0.0169***	-0.0304***	0.0165***	0.0140***
	(-0.31)	(10.17)	(10.97)	(-4.15)	(10.55)	(9.77)	(-5.49)	(4.27)	(4.97)	(-8.83)	(4.85)	(4.12)
Fragility	-0.277***	0.00554***	-0.0803	0.397***	-0.00143***	-0.00399***	-0.0853***	0.00200***	0.114***	0.116***	-0.000528***	-0.00108***
	(-27.34)	(12.27)	(-1.21)	(33.88)	(-6.65)	(-13.75)	(-33.81)	(16.68)	(5.77)	(38.52)	(-7.02)	(-15.68)
Panel D3: Opacity ($OPQFKN$) and Fragility, CATNONFAT												
	SFA						GFA					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.605***	0.923***	0.837***	0.558***	0.858***	0.911***	0.185***	0.278***	0.247***	0.177***	0.247***	0.267***
	(11.59)	(16.28)	(14.81)	(10.62)	(14.77)	(16.24)	(11.73)	(16.95)	(14.83)	(11.19)	(14.56)	(16.40)
Fragility	-0.266***	0.00661***	-0.0139	0.367***	-0.00140***	-0.00455***	-0.0772***	0.00226***	0.115***	0.0998***	-0.000480***	-0.00121***
	(-27.73)	(14.47)	(-0.21)	(33.15)	(-6.53)	(-15.69)	(-33.74)	(19.39)	(5.86)	(35.02)	(-6.48)	(-18.13)

B.2.5. Split Sample Analysis by Size

This section conducts the analysis separately for the first and fourth quartiles of the bank population split by bank size in the spirit of Berger and Bouwman (2009). The findings on opacity are somewhat stronger for small banks (Table B.33, Panel A) than large banks (Panel B). For large banks, $OOAJLY$ is insignificant except when $CATNONFAT$ and GFA parametrize intermediation quality (Panel D2). $OLNJLY$ is significantly negative for large banks in the $CATFAT$ cases but significantly positive in the $CATNONFAT$ cases. Finally, $OPQFKN$ is significantly positively associated with intermediation quality in Panels A2, C2 and D2. Hence, overall, opacity is positively associated with intermediation quality in most cases in both subsamples and hypothesis A3 is again rejected.

Table B.33.:
Intermediation Quality and Opacity, Split Sample Analysis by Bank Size.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT					
Panel A1: 1st Quartile			*Panel A2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.745***	0.267***	0.803***	0.0288	-0.127***	0.745***
(14.69)	(25.51)	(13.52)	(0.48)	(-4.81)	(6.81)
Panel B: GFA, CATFAT					
Panel B1: 1st Quartile			*Panel B2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.0982***	-0.00373***	0.101***	0.0237	-0.130***	-0.0663
(12.20)	(-2.68)	(12.39)	(0.82)	(-11.91)	(-1.37)

Continued on next page

Table B.33 – *Continued from previous page*

Panel C: SFA, CATNONFAT

Panel C1: 1st Quartile			*Panel C2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.465***	0.130***	0.520***	-0.0424	0.0540**	0.643***
(14.58)	(18.85)	(13.97)	(-0.72)	(2.19)	(5.96)

Panel D: GFA, CATNONFAT

Panel D1: 1st Quartile			*Panel D2: 4th Quartile*		
$OOAJLY$	$OLNJLY$	$OPQFKN$	$OOAJLY$	$OLNJLY$	$OPQFKN$
0.0735***	0.0199***	0.0780***	0.114***	0.0798***	0.315***
(17.64)	(24.88)	(17.38)	(4.15)	(7.64)	(7.43)

The analysis of fragility is reported in Table B.34 and shows that there are no major differences between small and large banks when it comes to the influence of fragility on intermediation quality. Only in the $CATFAT$ and GFA case do $LAGTA$, $LEVRAG$ and $ZIND_{pool}$ lose significance. Otherwise coefficients are as in the main analysis for both subsamples. Hence the bulk of the evidence still supports the rejection of A1.

Table B.34.: Intermediation Quality and Fragility, Split Sample Analysis by Bank Size.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

Panel A: SFA, CATFAT											
Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.279***	0.00439***	0.346***	0.331***	-0.00183***	-0.00240***	-0.0334	0.000269	0.272*	0.189***	-0.00131*	-0.000325
(-34.33)	(9.16)	(4.38)	(33.01)	(-5.99)	(-8.72)	(-1.18)	(0.25)	(1.72)	(6.36)	(-1.95)	(-0.34)
Panel B: GFA, CATFAT											
Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0281***	0.00178***	-0.00226	0.0255***	-0.000285***	-0.000876***	-0.136***	0.00553***	0.243***	0.183***	-0.00165***	-0.00379***
(-30.19)	(29.32)	(-0.24)	(18.34)	(-7.13)	(-26.16)	(-18.20)	(15.02)	(4.02)	(21.39)	(-4.63)	(-15.30)
Panel C: SFA, CATNONFAT											
Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.148***	0.00244***	0.201***	0.168***	-0.000982***	-0.00151***	-0.151***	0.00304***	0.657***	0.274***	-0.00231***	-0.00252***
(-27.74)	(7.96)	(4.17)	(26.50)	(-5.13)	(-8.45)	(-6.24)	(3.03)	(4.94)	(10.30)	(-3.61)	(-2.94)
Panel D: GFA, CATNONFAT											
Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
-0.0239***	0.000841***	0.0493***	0.0211***	-0.000253***	-0.000441***	-0.130***	0.00312***	0.301***	0.176***	-0.00140***	-0.00238***
(-40.54)	(24.54)	(7.65)	(29.54)	(-6.97)	(-24.32)	(-18.55)	(8.79)	(5.28)	(22.55)	(-5.74)	(-9.53)

The final tables (B.35-B.37) show that the findings noted above are robust to the inclusion of both opacity and fragility into the analysis. First, when considering $OOAJLY$, this variable is now mostly significantly positive for small banks. While this also holds for large banks when intermediation quality is parametrized using $CATNONFAT$ and GFA (Panel D2), this variable is mostly insignificant but positive for large banks. This mirrors the results obtained in Table B.33. Moreover, with the exception of NPL in the small bank subsample when GFA and $CATFAT$ determine intermediation quality, the fragility results are strong and in line with the main analysis. The same holds for large banks with the exception of Panel A2, where SFA and $CATFAT$ parametrize the frontier. Here, $LAGTA$, $LEVRAG$ and $ZIND_{pool}$ lose significance while all other variables maintain signs and significances. This is, at least in part, confirmed by the analysis of $OLNJLY$. Here, results for small banks are generally as in the main analysis, that is opacity and fragility are beneficial for intermediation quality. Concretely, $OLNJLY$ is significantly positively associated with intermediation quality, except when this is parametrized with GFA and $CATFAT$. Similarly, for large banks, $OLNJLY$ is negatively associated with intermediation quality when $CATFAT$ underlies the frontier. In contrast, the relation is often significantly positive when $CATNONFAT$ is used to obtain the frontier. This again mirrors Table B.33. Moreover, there is no apparent qualitative difference in the findings for fragility between small and large banks. Finally, results for $OPQFKN$ are entirely as in the main analysis for both small and large banks. This also holds qualitatively for the fragility results.

Table B.35.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by Bank Size, Opacity Based on $OOAJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1^{st} Quartile						*Panel A2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.346***	0.743***	0.734***	0.400***	0.789***	0.746***	0.0406	0.0300	0.0278	0.0384	0.0381	0.0313
	(8.36)	(14.97)	(14.53)	(9.49)	(15.04)	(15.07)	(0.67)	(0.49)	(0.46)	(0.65)	(0.63)	(0.51)
Fragility	-0.268***	0.00438***	0.249***	0.315***	-0.00143***	-0.00241***	-0.0353	0.000313	0.270*	0.190***	-0.00127*	-0.000368
	(-33.27)	(9.44)	(3.24)	(31.75)	(-4.94)	(-9.05)	(-1.23)	(0.28)	(1.70)	(6.37)	(-1.90)	(-0.39)
	Panel B: GFA, CATFAT											
	Panel B1: 1^{st} Quartile						*Panel B2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.0593***	0.0977***	0.0988***	0.0735***	0.101***	0.0988***	0.0702**	0.0440	0.0228	0.0329	0.0256	0.0500*
	(7.79)	(13.58)	(12.20)	(9.28)	(12.36)	(13.91)	(2.56)	(1.48)	(0.79)	(1.24)	(0.89)	(1.69)
Fragility	-0.0261***	0.00177***	-0.0153*	0.0225***	-0.000235***	-0.000877***	-0.140***	0.00559***	0.242***	0.183***	-0.00163***	-0.00386***
	(-27.11)	(30.12)	(-1.67)	(15.81)	(-6.27)	(-26.73)	(-18.87)	(14.94)	(3.99)	(21.47)	(-4.56)	(-15.28)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1^{st} Quartile						*Panel C2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.258***	0.465***	0.459***	0.294***	0.494***	0.466***	0.00812	-0.0315	-0.0448	-0.0287	-0.0393	-0.0254
	(9.13)	(14.84)	(14.38)	(10.19)	(14.93)	(14.98)	(0.14)	(-0.53)	(-0.77)	(-0.50)	(-0.66)	(-0.43)
Fragility	-0.140***	0.00243***	0.141***	0.156***	-0.000735***	-0.00152***	-0.151***	0.00300***	0.659***	0.273***	-0.00235***	-0.00249***
	(-26.35)	(8.18)	(2.99)	(24.99)	(-4.01)	(-8.74)	(-6.17)	(2.99)	(4.95)	(10.28)	(-3.66)	(-2.89)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1^{st} Quartile						*Panel D2: 4^{th} Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OOAJLY$	0.0398***	0.0732***	0.0718***	0.0527***	0.0758***	0.0738***	0.160***	0.126***	0.113***	0.123***	0.111***	0.132***
	(11.24)	(19.26)	(17.30)	(13.88)	(17.76)	(19.63)	(6.19)	(4.49)	(4.13)	(4.86)	(4.05)	(4.66)
Fragility	-0.0226***	0.000839***	0.0399***	0.0189***	-0.000215***	-0.000442***	-0.137***	0.00330***	0.294***	0.177***	-0.00131***	-0.00256***
	(-38.23)	(25.57)	(6.33)	(26.69)	(-6.19)	(-25.22)	(-19.41)	(9.24)	(5.20)	(22.59)	(-5.43)	(-10.30)

Table B.36.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by Bank Size, Opacity Based on $OLNJLY$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Jones, Lee and Yeager (2012). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0993***	0.259***	0.268***	0.131***	0.270***	0.259***	-0.153***	-0.127***	-0.128***	-0.237***	-0.135***	-0.127***
	(9.22)	(25.07)	(25.61)	(12.72)	(25.12)	(25.02)	(-6.02)	(-4.81)	(-4.88)	(-9.29)	(-5.06)	(-4.84)
Fragility	-0.240***	0.00316***	-0.00802	0.268***	-0.00120***	-0.00168***	-0.0705**	0.000258	0.308**	0.276***	-0.00144**	-0.000437
	Panel B: GFA, CATFAT											
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	-0.0324***	-0.00836***	-0.00378***	-0.0221***	-0.00253*	-0.00840***	-0.199***	-0.130***	-0.131***	-0.238***	-0.133***	-0.134***
	(-22.25)	(-6.70)	(-2.69)	(-14.99)	(-1.81)	(-6.74)	(-18.85)	(-11.75)	(-12.06)	(-23.83)	(-12.13)	(-12.07)
Fragility	-0.0409***	0.00181***	0.00272	0.0361***	-0.000291***	-0.000899***	-0.185***	0.00552***	0.280***	0.269***	-0.00178***	-0.00391***
	(-37.56)	(29.83)	(0.29)	(22.81)	(-7.22)	(-26.62)	(-25.51)	(15.05)	(4.74)	(33.03)	(-5.15)	(-15.51)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.0364***	0.125***	0.130***	0.0590***	0.132***	0.124***	-0.00281	0.0541**	0.0514**	-0.0650***	0.0513**	0.0516**
	(4.95)	(18.43)	(18.87)	(8.37)	(18.60)	(18.32)	(-0.12)	(2.20)	(2.09)	(-2.61)	(2.08)	(2.09)
Fragility	-0.134***	0.00184***	0.0300	0.140***	-0.000678***	-0.00117***	-0.152***	0.00305***	0.642***	0.297***	-0.00226***	-0.00248***
	(-22.05)	(6.36)	(0.66)	(20.85)	(-3.71)	(-7.03)	(-6.19)	(3.05)	(4.86)	(10.76)	(-3.54)	(-2.89)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OLNJLY$	0.00429***	0.0180***	0.0195***	0.0121***	0.0198***	0.0179***	0.0344***	0.0800***	0.0787***	0.0110	0.0778***	0.0776***
	(5.05)	(24.15)	(24.29)	(13.95)	(24.35)	(24.17)	(3.26)	(7.69)	(7.53)	(1.08)	(7.46)	(7.51)
Fragility	-0.0222***	0.000755***	0.0236***	0.0152***	-0.000207***	-0.000391***	-0.121***	0.00312***	0.279***	0.172***	-0.00133***	-0.00232***
	(-31.79)	(23.51)	(3.74)	(18.79)	(-6.17)	(-23.40)	(-16.95)	(8.90)	(4.78)	(21.89)	(-5.59)	(-9.23)

Table B.37.: Intermediation Quality, Opacity and Fragility, Split Sample Analysis by Bank Size, Opacity Based on $OPQFKN$.

Coefficients from Tobit regressions using fixed time effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. Opacity is based on Flannery, Kwan and Nimalendran (2013). Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: SFA, CATFAT											
	Panel A1: 1st Quartile						*Panel A2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.304***	0.797***	0.796***	0.389***	0.855***	0.794***	0.749***	0.821***	0.746***	0.718***	0.740***	0.821***
	(6.17)	(13.70)	(13.42)	(7.82)	(13.87)	(13.71)	(6.80)	(6.76)	(6.81)	(6.60)	(6.72)	(6.57)
Fragility	-0.270***	0.00432***	0.296***	0.317***	-0.00146***	-0.00235***	-0.0355	0.00222*	0.274*	0.186***	-0.00113*	-0.00165
	(-33.29)	(9.30)	(3.84)	(31.79)	(-4.98)	(-8.82)	(-1.26)	(1.89)	(1.74)	(6.30)	(-1.69)	(-1.64)
	Panel B: GFA, CATFAT											
	Panel B1: 1st Quartile						*Panel B2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.0525***	0.0986***	0.102***	0.0714***	0.104***	0.0980***	-0.0508	0.133***	-0.0661	-0.0933**	-0.0770	0.118**
	(6.83)	(13.71)	(12.39)	(8.89)	(12.50)	(13.71)	(-1.11)	(2.75)	(-1.37)	(-2.09)	(-1.59)	(2.48)
Fragility	-0.0264***	0.00177***	-0.00855	0.0229***	-0.000240***	-0.000870***	-0.136***	0.00584***	0.243***	0.183***	-0.00167***	-0.00398***
	(-27.86)	(29.85)	(-0.93)	(16.27)	(-6.37)	(-26.41)	(-18.14)	(15.37)	(4.01)	(21.40)	(-4.67)	(-15.85)
	Panel C: SFA, CATNONFAT											
	Panel C1: 1st Quartile						*Panel C2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.261***	0.516***	0.516***	0.315***	0.552***	0.514***	0.660***	0.812***	0.644***	0.603***	0.635***	0.821***
	(7.85)	(14.14)	(13.86)	(9.32)	(14.25)	(14.17)	(6.17)	(7.00)	(5.97)	(5.59)	(5.85)	(6.99)
Fragility	-0.140***	0.00239***	0.169***	0.157***	-0.000742***	-0.00148***	-0.153***	0.00497***	0.658***	0.271***	-0.00216***	-0.00384***
	(-26.27)	(8.05)	(3.59)	(24.97)	(-4.02)	(-8.53)	(-6.33)	(4.70)	(4.96)	(10.23)	(-3.41)	(-4.33)
	Panel D: GFA, CATNONFAT											
	Panel D1: 1st Quartile						*Panel D2: 4th Quartile*					
	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$	$LAGTA$	$LEVRAG$	NPL	$CREDRSK$	$ZIND_{MA(3)}$	$ZIND_{pool}$
$OPQFKN$	0.0357***	0.0767***	0.0768***	0.0529***	0.0805***	0.0763***	0.330***	0.458***	0.315***	0.289***	0.306***	0.460***
	(9.21)	(18.69)	(17.17)	(12.88)	(17.31)	(18.73)	(8.27)	(10.50)	(7.43)	(7.20)	(7.16)	(10.68)
Fragility	-0.0228***	0.000834***	0.0446***	0.0191***	-0.000218***	-0.000436***	-0.131***	0.00420***	0.302***	0.175***	-0.00133***	-0.00312***
	(-38.25)	(25.33)	(7.06)	(26.86)	(-6.23)	(-24.92)	(-18.90)	(11.59)	(5.33)	(22.61)	(-5.52)	(-12.62)

B.2.6. Analysis Using Raw Liquidity Creation as Dependent Variable

Generally this thesis has chosen to approach the econometric challenge of investigating the relation between bank intermediation and opacity and fragility by focusing on an alternative measure of intermediation, specifically intermediation quality. In that sense the issue is being approached from the perspective of the dependent variable. However these challenges could also be approached from the perspective of the independent variables. More specifically, to avoid regressions of an all encompassing balance sheet measure of liquidity creation on balance sheet indicators of opacity and fragility, one could construct alternative opacity and fragility measures from the available data.

This section summarizes the results that obtain when various indices are used to proxy for opacity and fragility. Specifically, I use four ways of creating indices.

1. Principal Components Analysis: I consider the first ($OPPCA1$, $FRAGPCA1$) or second components ($OPPCA2$, $FRAGPCA2$).
2. Simple sums across the opacity/fragility variables ($OPSUM$, $FRAGSUM$).
3. Ranks based on the sums across the opacity/fragility variables ($OPRKS$, $FRAGRKS$).
4. Average of the ranks obtained for each opacity/fragility variable in turn ($OPRKA$, $FRAGRKA$).

In the case of PCA and opacity I obtain the following components and loadings. The first component explains a sizeable 51% of the variation across $OOAJLY$, $OLNJLY$ and $OPQFKN$. Moreover it loads strongly positively on $OOAJLY$ and $OPQFKN$ which is plausible. The low negative loading on $OLNJLY$ is unexpected however. The second component contributes another 33% to the picture. It loads positively on all three opacity variables but focuses mostly on $OLNJLY$.

Table B.38.: Factor Loadings for Opacity Variables.

For opacity $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively.

Variable	$C1$	$C2$	$C3$
$OOAJLY$	0.7052	0.0502	0.7072
$OLNJLY$	-0.0750	0.9972	0.0040
$OPQFKN$	0.7050	0.0559	-0.7070

In terms of fragility, the following components and loadings result. The first component explains 35% of the common variation in $LAGTA$, $LEVRAG$, NPL, $CREDRSK$, $ZIND_{MA(3)}$ and $ZIND_{pool}$, while the second contributes another 21%. The loadings on the first principal component are fully consistent with the interpretation as a risk factor. Specifically, $LAGTA$ and the Z-Scores load negatively while the other variables load positively on this component, all consistent with greater fragility. The loadings on the second component reverse sign for $LEVRAG$ and $ZIND_{pool}$ and are hence somewhat less consistent with a risk interpretation. However the positive loading on $ZIND_{pool}$ may be due to the fact that for this variable volatility of the return on assets is computed across all banks. Hence it is not exclusively indicative of bank-level risk.

Table B.39.: Factor Loadings for Fragility Variables.

For fragility $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations.

Variable	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
$LAGTA$	-0.4658	-0.3167	-0.0552	0.3894	0.7169	0.1188
$LEVRAG$	0.4410	-0.6219	0.0017	-0.0917	-0.0441	0.6391
NPL	0.3260	0.3284	-0.0025	0.8506	-0.1396	0.2071
$CREDRSK$	0.3871	0.5422	0.0217	-0.3183	0.6228	0.2577
$ZIND_{MA(3)}$	-0.0361	-0.0263	0.9982	0.0303	0.0249	0.0027
$ZIND_{pool}$	-0.5754	0.3323	-0.0034	-0.1196	-0.2757	0.6842

The other metrics require little separate discussion. It is worth mentioning, however, that the simple summations that are the basis of the third index are carried out only after standardizing all variables by subtracting the mean and dividing by the standard deviation. Additionally, the summation uses the negative of $LAGTA$ and the Z-Scores because these are negatively associated with fragility. Moreover, the first ranking-based index is derived from the sum-based index. In addition, the ranks are subsequently standardized to avoid numerical problems that may obtain for variables that exhibit an extremely large range. The last ranking-based measure is computed by ranking banks on each opacity or fragility measure and then taking the average rank within the category. Thus, for example, in the case of opacity the ranks on $OOAJLY$, $OLNJLY$

and $OPQFKN$ are averaged to obtain the index. Similarly, the index value is then standardized.

Using these indices the analysis can be carried out using $CATFAT$ and $CATNONFAT$ as the dependent variables. It is adequate to use the quantities of liquidity creation directly as dependent variables when indices are constructed to proxy for opacity and fragility since the indices are much less likely to be trivially associated with the quantity of liquidity creation than the raw opacity and fragility proxies. The results reported in Table B.40 were obtained from a linear panel data model with bank and year fixed effects and data winsorized at the 0.01 and 0.99 percentiles. Winsorization at 0.02 and 0.98 percentiles does not affect results. The indices were computed after winsorizing.

The results in Panels A and B show both that opacity and fragility as proxied by the various indices is individually significantly positively associated with both $CATFAT$ and $CATNONFAT$. This is independent of the mechanism used to construct the opacity index.

Panels C1-C5 show that the individual results obtained for opacity and fragility are also upheld when both opacity and fragility are included among the independent variables. Overall this emphatically confirms that opacity and fragility are significantly positively associated with bank intermediation.

Table B.40.: Bank Intermediation, Opacity and Fragility, Analysis Using Fixed Effects Regression.

Coefficients from fixed effects regressions using fixed bank and time effects and standard errors clustered by bank. The dependent variable is liquidity creation using Berger and Bouwman's (2009) $CATFAT$ and $CATNONFAT$ metrics. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. All regressions include the following control variables: the log of gross total assets, the return on assets, cost efficiency parametrized by way of SFA, dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company, dummy variables set to 1 if the bank was merged (acquired) within the last three years, bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. The main variables of interest are indices of opacity and fragility. Specifically, $xPCA1$ and $xPCA2$ are the first two principal components of opacity when $x = OP$ and fragility when $x = FRAG$. $xSUM$ is the normalized sum of the opacity respectively fragility variables, $xRKS$ is the normalized rank obtained from the sum of the opacity respectively fragility variables. Finally, $xRKA$ is the average of the ranks of the opacity and fragility variables. These indices are constructed using the following base variables. For fragility $LAGTA$ is the ratio of liquid assets over total assets. $CREDRSK$ is the quantity of risk weighted assets over total assets. $LEVRAG$ stands for leverage, NPL stands for the ratio of nonperforming loans over total loans, $ZIND_{pool}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed across the pooled sample of banks, $ZIND_{MA(3)}$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $OOAJLY$ and $OLNJLY$ represent opaque assets following Jones, Lee and Yeager (2012) and $OPQFKN$ represents opaque assets following Flannery, Kwan and Nimalendran (2013) respectively. Monetary values are in 2005 US Dollars. Variables are winsorized at the 0.01 and 0.99 percentiles.

	Panel A: Opacity									
	CATFAT					CATNONFAT				
	$OPPCA1$	$OPPCA2$	$OPSUM$	$OPRKS$	$OPRKA$	$OPPCA1$	$OPPCA2$	$OPSUM$	$OPRKS$	$OPRKA$
Opacity	0.00979***	0.0657***	0.0166***	0.0368***	0.0355***	0.00913***	0.0601***	0.0154***	0.0344***	0.0331***
	(13.11)	(51.70)	(36.85)	(43.98)	(43.51)	(12.92)	(52.19)	(36.98)	(45.22)	(44.92)
	Panel B: Fragility									
	CATFAT					CATNONFAT				
	$OPPCA1$	$OPPCA2$	$OPSUM$	$OPRKS$	$OPRKA$	$OPPCA1$	$OPPCA2$	$OPSUM$	$OPRKS$	$OPRKA$
Fragility	0.0537***	0.0308***	0.0158***	0.0618***	0.0650***	0.0516***	0.0284***	0.0155***	0.0592***	0.0621***
	(68.43)	(37.99)	(49.47)	(72.83)	(81.14)	(75.46)	(38.41)	(52.43)	(79.88)	(87.78)
	Panel C1: Opacity ($OPPCA1$) and Fragility									
	CATFAT					CATNONFAT				
	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$
$OPPCA1$	0.0190***	0.00529***	0.0146***	0.0153***	0.0140***	0.0180***	0.00505***	0.0138***	0.0144***	0.0131***
	(27.27)	(6.93)	(21.68)	(23.06)	(21.47)	(27.93)	(7.10)	(21.90)	(23.12)	(21.25)
Fragility	0.0573***	0.0296***	0.0165***	0.0645***	0.0668***	0.0550***	0.0272***	0.0161***	0.0617***	0.0638***
	(75.63)	(35.69)	(50.57)	(78.10)	(84.70)	(83.43)	(36.11)	(53.28)	(85.33)	(91.44)

Continued on next page

Table B.40 – *Continued from previous page*

Panel C2: Opacity ($OPPCA2$) and Fragility

	CATFAT					**CATNONFAT**				
	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$
$OPPCA2$	0.0509***	0.0603***	0.0558***	0.0540***	0.0520***	0.0458***	0.0552***	0.0502***	0.0487***	0.0468***
	(42.98)	(47.62)	(46.94)	(45.96)	(44.65)	(44.23)	(48.20)	(47.71)	(46.89)	(45.41)
frag	0.0453***	0.0226***	0.0131***	0.0523***	0.0546***	0.0440***	0.0209***	0.0131***	0.0505***	0.0528***
	(62.47)	(29.90)	(45.86)	(66.08)	(71.65)	(70.00)	(30.04)	(49.20)	(73.41)	(78.49)

Panel C3: Opacity ($OPSUM$) and Fragility

	CATFAT					**CATNONFAT**				
	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$
$OPSUM$	0.0182***	0.0137***	0.0170***	0.0170***	0.0160***	0.0169***	0.0127***	0.0157***	0.0158***	0.0147***
	(48.39)	(29.06)	(44.74)	(45.44)	(43.19)	(50.48)	(29.41)	(46.31)	(46.91)	(44.29)
Fragility	0.0550***	0.0242***	0.0160***	0.0624***	0.0641***	0.0528***	0.0222***	0.0156***	0.0597***	0.0613***
	(77.76)	(29.66)	(51.05)	(79.09)	(84.32)	(86.76)	(29.98)	(53.96)	(87.06)	(91.93)

Panel C4: Opacity ($OPRKS$) and Fragility

	CATFAT					**CATNONFAT**				
	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$
$OPRKS$	0.0348***	0.0318***	0.0343***	0.0340***	0.0321***	0.0326***	0.0299***	0.0320***	0.0317***	0.0299***
	(48.49)	(37.24)	(47.02)	(47.20)	(44.92)	(51.32)	(38.52)	(49.42)	(49.61)	(47.15)
Fragility	0.0522***	0.0244***	0.0152***	0.0597***	0.0617***	0.0503***	0.0224***	0.0149***	0.0572***	0.0591***
	(72.68)	(30.68)	(49.69)	(74.95)	(81.22)	(81.24)	(30.87)	(52.78)	(82.89)	(88.71)

Panel C5: Opacity ($OPRKA$) and Fragility

	CATFAT					**CATNONFAT**				
	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$	$FRAGPCA1$	$FRAGPCA2$	$FRAGSUM$	$FRAGRKS$	$FRAGRKA$
$OPRKA$	0.0331***	0.0309***	0.0327***	0.0321***	0.0304***	0.0309***	0.0290***	0.0304***	0.0299***	0.0283***
	(46.82)	(37.20)	(45.50)	(45.18)	(42.96)	(49.82)	(38.56)	(48.02)	(47.68)	(45.20)
Fragility	0.0520***	0.0252***	0.0152***	0.0594***	0.0616***	0.0501***	0.0231***	0.0149***	0.0569***	0.0590***
	(72.04)	(31.82)	(49.56)	(74.30)	(80.96)	(80.29)	(32.03)	(52.60)	(82.01)	(88.25)

C. Appendix to Chapter 5

This appendix provides additional analyses and robustness checks for the results reported in Chapter 5. Specifically, Section C.1 tabulates and discusses a variety of different specifications of managerial ability, while Section C.2 tabulates the results of various robustness checks.

C.1. Various Managerial Ability Specifications

This section replicates the main analysis for a number of different managerial ability specifications in order to investigate the robustness of the main results. It is similar in structure to the main analysis. Thus Section C.1.1 discusses various managerial ability specifications and Section C.1.2 assesses their validity. Sections C.1.3 and C.1.4 report the findings on the various hypothesis tests.

C.1.1. Deriving Managerial Ability

As in the main analysis, this section uses efficiency scores to obtain managerial ability by way of purging bank-specific effects from the efficiency scores. Concretely, this section runs the regression in Equation C.1 with $r = 1$ as the baseline case. r defines the set of regressors used to obtain managerial ability from efficiency scores. It also augments or changes the set of regressors as needed to obtain Specifications $r = 2$ and $r = 3$. The various specifications are discussed below. This is done for four types of efficiency (m), also discussed further below. In addition, each of these twelve specifications is run both for pooled data with year fixed effects ($s = p$) and for yearly ($s = y$) data. The residual, $MA^r_{m,s}$, captures all effects that are specific to the manager and not the bank for the parametrization.[1]

$$m_{i,t} = \alpha + \boldsymbol{\xi}'\mathbf{z}^r_{i,t} + \sum_{t=1}^{15} \theta_t d_t + MA^r_{m,s,i,t}. \tag{C.1}$$

[1] The set of subscripts ${}^r_{m,s}$ should, for completeness, also be attached to the coefficients. However, since there is little room for ambiguity and writing out these indices would clutter the notation, this thesis suppresses these indices.

Here, m represents the efficiency score used to obtain managerial ability, where $m \in \{\tau - \text{eff}_{DEA}, \tau - \text{eff}_{SFA}, \tau - \text{eff}_{GFA}, \pi - \text{eff}_{DEA}\}$. $\tau - \text{eff}$ denotes revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. In terms of regressors, $\mathbf{z}^r_{i,t}$, the baseline specification ($r = 1$) contains year fixed effects, θ, and the following controls: $BKSIZE$ is the log of gross total assets, $NUMEMP$ is the log of the number of full time equivalent employees in thousands, AGE is the log of the age of the bank in years, $LEVRAG$ represents leverage and FCF is an indicator variable that takes the value one when cash flow for the year is positive.

It has been noted in the empirical banking literature (Berger and Bouwman, 2009), that the status of a commercial bank as a member of a bank holding company is significant, for example because this status affords the member bank greater access to resources. The individual bank manager is unlikely to be able to influence the BHC membership status, certainly not in the short run. Moreover, managers whose banks are part of a BHC are likely to be subject to strategic guidelines from the holding company. Therefore this section argues that BHC membership is an important bank-specific attribute, unique to the banking industry, and therefore should be included in the model. Hence Specification $r = 2$ augments the regression by adding $MBHC$ and $OBHC$ to $\mathbf{z}$. These are dummy variables that take the value 1 if, during the last three years, the bank is a multi-bank (one-bank)-holding company member respectively. Additionally, the selection of covariates in Specification $r = 1$, suggested by Cantrell (2013) and Demerjian, Lev and McVay (2012), may itself invite skepticism. Thus Demerjian, Lev and McVay (2012) argue that the Tobit regressions are intended to purge the efficiency scores of influences that are due to the bank and not to the manager. However, $LEVRAG$, $NUMEMP$ and $BKSIZE$ are certainly influenced by managerial decision making both in the short and the long term. For this reason Specification $r = 3$ omits these variables and replaces them with a different set of regressors. These are less likely to be subject to managerial discretion, at least in the short term, and thus more appropriately align with the Demerjian, Lev and McVay-methodology. Specifically, this specification includes the bank-level Herfindahl-Hirschmann index ($BKHHI$), the log bank-level population ($BKPOP$), population density ($BKPDNS$), percent income growth rates ($BKICHG$) as well as the market share of medium and large banks in the area ($BKMSML$).

In the main analysis the regression to obtain managerial ability used DEA-based profit efficiency ($\pi - \text{eff}_{DEA}$) and the set of regressors suggested by Demerjian, Lev and McVay (2012) and Cantrell (2013). The underlying assumption of this approach is that the managerial objective is, in fact, profit maximization. The main analysis follows this approach because, intuitively, profit maximization seems to be the natural managerial objective. However this is not the kind of MA measure that has been investigated in the prior literature and has been shown to subsume information otherwise inherent in manager fixed effects, for instance. Therefore it is necessary to recognize that the ultimate managerial objective may, for example, be revenue maximization as postulated by Demerjian, Lev and McVay (2012). Hence, as a further robustness check, this section also examines results obtained from various revenue efficiency measures. Specifically, I consider revenue efficiency based on SFA, DEA and GFA.

Finally, the Demerjian, Lev and McVay (2012)-methodology advocates a pooled Tobit regression approach ($s = p$). The main analysis estimates MA based on each yearly subsample ($s = y$) in order to avoid look-ahead bias. Therefore this Section replicates the main analysis with pooled sample regressions. Overall, this gives twenty four different specifications of managerial ability, $MA^r_{m,s}$.

Table C.1 reports an example of the yearly regression ($s = y$). Specifically, it reports regression results for the year 2004 for each of the twelve combinations between dependent variable, m, and set of regressors, r. Results for pooled regressions are also reported in Table C.2.

First, I discuss the findings for the yearly regressions. Table C.1 is organized in four panels, each devoted to a particular efficiency score as the basis for managerial ability. Specifically, Panel A is based on revenue efficiency parametrized by way of DEA ($\tau - \text{eff}_{DEA}$), Panel B uses SFA ($\tau - \text{eff}_{SFA}$) and Panel C uses GFA ($\tau - \text{eff}_{GFA}$). Finally, Panel D uses profit efficiency obtained from DEA as its efficiency specification ($\pi - \text{eff}_{DEA}$) and replicates the results given in the main analysis. Each panel has three columns, which represent different sets of regressors. Specification 1 uses the original regressors from Demerjian, Lev and McVay (2012) and Cantrell (2013), Specification 2 adds bank holding company status variables and Specification 3 removes potentially unsuitable regressors and replaces them by bank demographic variables as discussed above. Results show similar coefficients in Specifications 1 and 2 across Panels A, B and D as well as for Specification 3 across Panels A, C and D. Overall, more efficient banks tend to be older (AGE), bigger ($BKSIZE$) more highly leveraged ($LEVRAG$) and generate more cash flow (FCF) with smaller workforce ($NUMEMP$). Among the bank demographic variables substantial similarities obtain only for $BKPOP$, $BKMSML$ and $BKPDNS$, which generally indicate that more efficient banks are active in less populous markets with fewer medium and large banks. It is not surprising that the use of different efficiency scores as the dependent variable results in different coefficients on the regressors since different efficiency parametrization methods will tend to pick

Table C.1.: Regression Results for Managerial Ability, Yearly Regressions.

Coefficients from yearly Tobit regressions for the year 2004. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. The dependent variable is given in the panel header. $BKSIZE$ stands for the natural log of gross total assets, $NUMEMP$ is the natural log of the number of thousand full-time equivalent employees, AGE is the log of bank age, $LEVRAG$ is the leverage of the bank. $MBHC$ and $OBHC$ are dummy variables that identify the firm as a multibank or onebank holding company member. FCF is an indicator variable that takes the value 1 when there is free cash flow for a bank in a given year. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Specification (1) uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification (2) adds the holding company status variables, Specification (3) avoids potentially endogenous variables alltogether and substitutes bank demographic variables. $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A:$\tau -$ eff$_{DEA}$			**Panel B:**$\tau -$ eff$_{SFA}$			**Panel C:**$\tau -$ eff$_{GFA}$			**Panel D:**$\pi -$ eff$_{DEA}$		
Parameter	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$BKSIZE$	0.0310***	0.0295***		0.0532***	0.0567***		-0.0404***	-0.0407***		0.0677***	0.0636***	
	(5.53)	(5.26)		(6.99)	(7.35)		(-17.39)	(-17.15)		(8.72)	(8.16)	
$NUMEMP$	-0.0492***	-0.0476***		-0.0231***	-0.0282***		0.0112***	0.0111***		-0.0836***	-0.0801***	
	(-8.64)	(-8.30)		(-3.02)	(-3.60)		(4.90)	(4.80)		(-10.45)	(-9.95)	
AGE	0.0116***	0.0119***	0.00969***	-0.0266***	-0.0284***	-0.0286***	0.00215***	0.00193***	-0.00267***	0.0196***	0.0195***	0.00623***
	(8.76)	(8.91)	(7.00)	(-12.39)	(-13.11)	(-12.18)	(4.34)	(3.80)	(-3.64)	(11.64)	(11.42)	(3.60)
$LEVRAG$	0.00132*	0.00149*		0.00687***	0.00584***		-0.00130***	-0.00144***		0.00387***	0.00371***	
	(1.65)	(1.85)		(6.73)	(5.70)		(-5.00)	(-5.42)		(5.68)	(5.41)	
FCF	0.0220***	0.0223***	0.0231***	0.0181**	0.0146*	0.0157*	0.00310	0.00234	0.000235	0.0394***	0.0374***	0.0289***
	(4.89)	(4.92)	(4.95)	(2.21)	(1.76)	(1.89)	(1.28)	(0.96)	(0.09)	(6.45)	(6.10)	(4.57)
$MBHC$		-0.00259	-0.00961**		0.0352***	0.0667***		0.00783***	-0.0201***		0.0209***	0.0179***
		(-0.54)	(-1.97)		(4.60)	(8.29)		(4.35)	(-8.63)		(3.83)	(3.18)
$OBHC$		-0.0104**	-0.0185***		0.0510***	0.0694***		0.00558***	-0.0106***		-0.00242	-0.0132***
		(-2.37)	(-4.32)		(8.11)	(10.55)		(4.06)	(-6.08)		(-0.50)	(-2.87)
$BKHHI$			-0.0164			0.0674***			-0.0399***			-0.0141
			(-1.18)			(3.55)			(-9.08)			(-0.97)
$BKMSML$			0.00967			-0.0501***			-0.0401***			-0.0162*
			(1.06)			(-3.39)			(-9.42)			(-1.68)
$BKPOP$			-0.00346***			0.0163***			-0.00620***			-0.0127***
			(-2.78)			(7.84)			(-10.83)			(-9.39)
$BKPDNS$			-0.00731***			0.0199***			-0.00451***			-0.00376**
			(-4.53)			(7.73)			(-7.55)			(-2.26)
$BKICHG$			0.0675			0.203***			-0.00940			-0.0457
			(1.61)			(3.15)			(-0.77)			(-1.10)
Constant	0.141***	0.156***	0.415***	0.140**	0.0982	0.440***	1.197***	1.198***	0.898***	-0.596***	-0.560***	0.174***
	(3.00)	(3.32)	(26.20)	(2.05)	(1.43)	(16.25)	(58.91)	(57.99)	(120.88)	(-9.04)	(-8.50)	(9.49)
N	6505	6505	6505	6505	6505	6505	6505	6505	6505	6505	6505	6505

up similar yet distinct information sets (Bauer, Berger, Ferrier and Humphrey, 1998). Therefore different combinations of the regressors are required to purge each of these scores of bank-specific influences.

Although somewhat more heterogeneous, the pooled Tobit regressions confirm many of the observations made above. Thus, size is still mostly positively associated with efficiency, albeit insignificantly in Panel A ($BKSIZE$). Age, leverage and free cash flow are still mostly positively associated with efficiency (AGE, $LEVRAG$, FCF). The bank demographic variables indicate that concentration of local bank markets ($BKHHI$), presence of medium and large banks ($BKMSML$) and market population ($BKPOP$, $BKPDNS$) are all mostly negatively related to bank efficiency. Overall, similarities notwithstanding some differences between the regression coefficients exist. This is natural, given the different dependent variables used to obtain them. These differences underpin the value of using various MA specifications as a robustness check.

Table C.2.: Regression Results for Managerial Ability, Pooled Regressions.

Coefficients from pooled Tobit regressions with time fixed effects. The dependent variable is given in the panel header. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. $BKSIZE$ stands for the natural log of gross total assets, $NUMEMP$ is the natural log of the number of thousand full-time equivalent employees, AGE is the log of bank age, $LEVRAG$ is the leverage of the bank. $MBHC$ and $OBHC$ are dummy variables that identify the firm as a multibank or onebank holding company member. FCF is an indicator variable that takes the value 1 when there is free cash flow for a bank in a given year. $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ are bank-level demographic variables calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and marketshare of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. Specification (1) uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification (2) adds the holding company status variables, Specification (3) avoids potentially endogenous variables alltogether and substitutes bank demographic variables. $\tau-$eff represents revenue efficiency, while $\pi-$eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A: $\tau-\text{eff}_{DEA}$			**Panel B:** $\tau-\text{eff}_{SFA}$			**Panel C:** $\tau-\text{eff}_{GFA}$			**Panel D:** $\pi-\text{eff}_{DEA}$		
Parameter	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$BKSIZE$	0.00536	0.00369		0.0556***	0.0591***		-0.0248***	-0.0248***		0.0720***	0.0687***	
	(1.57)	(1.08)		(11.64)	(12.22)		(-21.52)	(-21.33)		(27.14)	(25.62)	
$NUMEMP$	-0.0152***	-0.0134***		-0.0305***	-0.0342***		0.00392***	0.00384***		-0.0739***	-0.0717***	
	(-4.28)	(-3.78)		(-6.43)	(-7.12)		(3.50)	(3.36)		(-26.51)	(-25.58)	
AGE	0.0112***	0.0118***	0.00926***	-0.0236***	-0.0251***	-0.0249***	-0.0000425	-0.000173	-0.00444***	0.0128***	0.0125***	0.00458***
	(14.98)	(15.71)	(12.23)	(-17.06)	(-17.78)	(-16.15)	(-0.16)	(-0.61)	(-11.35)	(21.15)	(20.52)	(8.54)
$LEVRAG$	0.00521***	0.00549***		0.00701***	0.00631***		0.000646***	0.000578***		0.00233***	0.00205***	
	(16.22)	(17.04)		(12.74)	(11.48)		(5.59)	(4.95)		(11.64)	(10.16)	
FCF	0.0162***	0.0172***	0.0144***	0.0313***	0.0285***	0.0265***	0.00368***	0.00342***	0.00413***	0.0203***	0.0193***	0.0114***
	(12.79)	(13.58)	(11.09)	(12.25)	(11.27)	(10.42)	(5.19)	(4.84)	(5.21)	(19.99)	(18.81)	(13.37)
$MBHC$		-0.00518**	-0.00323		0.0156***	0.0490***		0.00274***	-0.0157***		0.0206***	0.0261***
		(-2.10)	(-1.28)		(3.21)	(9.51)		(3.03)	(-13.33)		(10.98)	(17.17)
$OBHC$		-0.0151***	-0.0123***		0.0358***	0.0533***		0.00260***	-0.00598***		0.00172	-0.00263*
		(-6.87)	(-5.61)		(8.55)	(12.01)		(3.72)	(-7.04)		(1.17)	(-1.94)
$BKHHI$			-0.0279***			0.0790***			-0.0302***			-0.0162***
			(-4.59)			(6.39)			(-14.66)			(-5.21)
$BKMSML$			0.00726*			-0.0444***			-0.0307***			-0.00995***
			(1.86)			(-5.42)			(-15.26)			(-3.88)
$BKPOP$			-0.00296***			0.0147***			-0.00393***			-0.00761***
			(-5.01)			(11.69)			(-13.57)			(-19.37)
$BKPDNS$			-0.00395***			0.0204***			-0.00183***			-0.00103*
			(-4.40)			(10.91)			(-5.47)			(-1.92)
$BKICHG$			0.0143*			-0.0575***			-0.00594*			0.0330***
			(1.84)			(-4.24)			(-1.84)			(5.72)
Constant	0.271***	0.288***	0.394***	0.127***	0.0910**	0.466***	1.045***	1.044***	0.871***	-0.637***	-0.608***	0.0963***
	(9.68)	(10.30)	(48.65)	(2.97)	(2.12)	(26.47)	(100.78)	(100.52)	(209.91)	(-28.59)	(-27.00)	(18.73)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	100976	100976	100962	100976	100976	100962	100976	100976	100962	100976	100976	100962

C.1.2. Validation of Managerial Ability

To validate the various parametrizations of MA and to gain first insight into the relations between MA and bank behavior, this section investigates the correlations that obtain between the various parametrizations of managerial ability and indicators of bank value creation and risk. As in the main analysis, ROA and ROE as well as the ratio of EVA over total assets ($SHVR$) are the value indicators. The Z-Score ($ZIND$) and the standard deviation of ROA ($SDROA$), the ratio of risk weighted assets to total assets ($CREDRSK$), the ratio of nonperforming loans to total loans (NPL), the tier 1 ratio ($T1R$) and the ratio of liquid assets to total assets ($LAGTA$) indicate risk-taking. Table C.3 displays the results.

First, considering the value and profitability indicators, results show a remarkably robust picture. Regardless of the specification used, a highly significant and positive association between MA and all three value/profitability indicators obtains. The only exception is the specification that uses generalized frontier analysis and the third set of regressors to obtain managerial ability for both the yearly and pooled approach ($MA^3_{\tau-\text{eff}_{GFA},y}$ and $MA^3_{\tau-\text{eff}_{GFA},p}$). Regression results in Tables C.1 and C.2 indicated that GFA seems to be picking up somewhat different information than SFA and DEA, so that different correlations are not entirely surprising. Furthermore, reassuringly, the second stage regressions using regressor sets 1 and 2 deliver managerial ability scores that are consistent across methods (DEA, SFA and GFA). Overall, as expected, managerial ability appears to promote bank profitability respectively value creation.

Second, for the indicators of risk, the overall picture suggests that more ably managed banks are also more risky. Thus, for $CREDRSK$, all parametrizations of MA indicate that more ably managed banks hold greater quantities of risk weighted assets per unit of assets. In addition, the majority of MA specifications indicates that more ably managed banks have greater quantities of nonperforming loans per unit of loans (NPL) on the books, which suggests that they are more aggressive and thus possibly more risky. Furthermore, the results indicate that more ably managed banks are more aggressively capitalized; the tier 1 ratio $T1R$ is significantly negatively associated with MA. This holds with the exception of the MA parametrization that relies on DEA and revenue efficiency and regressor sets 1 and 2 ($MA^{1,2}_{\tau-\text{eff}_{DEA}}$) as well as the GFA revenue efficiency with regressor set 3 ($MA^3_{\tau-\text{eff}_{GFA}}$). Additionally and consistently across MA parametrizations, more ably managed banks appear to hold lower levels of liquid assets ($LAGTA$). Finally, most parametrizations indicate, albeit insignificantly, that more able management signals a greater distance to default as proxied by Z-Score and lower variation of ROA ($ZIND$ and $SDROA$ respectively). These variables, as in the main analysis, suggest that more ably managed banks are less risky. Hence a multivariate analysis is required to clarify this question.

Table C.3.: Correlations of Managerial Ability with General Performance Measures.

This table reports Pearson correlation coefficients of managerial ability and bank performance characteristics. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. ROA (ROE) stands for return on assets (equity). $CREDRSK$ is the quantity of risk weighted assets over total assets. NPL stands for the ratio of nonperforming loans over total loans, $ZIND$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each firm individually using the last three observations. The corresponding standard deviation of return on assets is given by $SDROA$. $T1R$ stands for the tier 1 ratio, while $LAGTA$ represents liquid assets scaled by total assets. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	ROA	ROE	$SHVR$	$CREDRSK$	NPL	$T1R$	$SDROA$	$ZIND$	$LAGTA$
$MA^1_{\tau-\text{eff}_{DEA},y}$	0.0494***	0.0257***	0.0249***	0.0517***	0.000866	0.0415***	0.0112***	0.00132	-0.0318***
$MA^1_{\tau-\text{eff}_{DEA},p}$	0.0466***	0.0195***	0.0230***	0.0481***	0.00504	0.0455***	0.0144***	0.000396	-0.0292***
$MA^2_{\tau-\text{eff}_{DEA},y}$	0.0524***	0.0286***	0.0269***	0.0550***	0.0000254	0.0382***	0.00956***	0.00153	-0.0333***
$MA^2_{\tau-\text{eff}_{DEA},p}$	0.0493***	0.0218***	0.0245***	0.0516***	0.00465	0.0422***	0.0135***	0.000596	-0.0306***
$MA^3_{\tau-\text{eff}_{DEA},y}$	0.0226***	0.0173***	0.0443***	0.0465***	0.0187***	-0.0195***	0.0215***	-0.00113	-0.0444***
$MA^3_{\tau-\text{eff}_{DEA},p}$	0.0236***	0.0186***	0.0461***	0.0457***	0.0158***	-0.0203***	0.0228***	-0.00184	-0.0430***
$MA^1_{\tau-\text{eff}_{SFA},y}$	0.0840***	0.0720***	0.1240***	0.1750***	0.0117***	-0.1160***	-0.0536***	0.00145	-0.2810***
$MA^1_{\tau-\text{eff}_{SFA},p}$	0.0799***	0.0665***	0.1190***	0.1780***	0.0147***	-0.1170***	-0.0510***	0.00157	-0.2830***
$MA^2_{\tau-\text{eff}_{SFA},y}$	0.0803***	0.0686***	0.1220***	0.1710***	0.0124***	-0.1110***	-0.0527***	0.00126	-0.2790***
$MA^2_{\tau-\text{eff}_{SFA},p}$	0.0763***	0.0632***	0.1170***	0.1740***	0.0155***	-0.1130***	-0.0499***	0.00136	-0.2820***
$MA^3_{\tau-\text{eff}_{SFA},y}$	0.0872***	0.0927***	0.1580***	0.2000***	0.00239	-0.1820***	-0.0604***	0.00294	-0.2980***

Continued on next page

Table C.3 – *Continued from previous page*

	ROA	ROE	$SHVR$	$CREDRSK$	NPL	$T1R$	$SDROA$	$ZIND$	$LAGTA$
$MA^3_{\tau-\text{eff}_{SFA},p}$	0.0867***	0.0913***	0.1570***	0.2010***	0.00426	-0.1810***	-0.0594***	0.00299	-0.3010***
$MA^1_{\tau-\text{eff}_{GFA},y}$	0.0416***	0.0404***	0.0548***	0.0400***	-0.00498	-0.0318***	-0.0328***	-0.000383	-0.0807***
$MA^1_{\tau-\text{eff}_{GFA},p}$	0.0187***	0.0118***	0.0428***	0.0297***	0.0276***	-0.0250***	-0.00465	-0.00201	-0.0753***
$MA^2_{\tau-\text{eff}_{GFA},y}$	0.0399***	0.0386***	0.0531***	0.0375***	-0.00478	-0.0290***	-0.0332***	-0.000323	-0.0793***
$MA^2_{\tau-\text{eff}_{GFA},p}$	0.0170***	0.00990***	0.0412***	0.0275***	0.0281***	-0.0224***	-0.00456	-0.00198	-0.0741***
$MA^3_{\tau-\text{eff}_{GFA},y}$	-0.0190***	-0.0270***	0.000154	-0.0285***	0.0308***	0.0286***	0.0148***	-0.00836***	-0.0378***
$MA^3_{\tau-\text{eff}_{GFA},p}$	-0.0267***	-0.0357***	-0.00110	-0.0323***	0.0441***	0.0282***	0.0254***	-0.00742**	-0.0379***
$MA^1_{\pi-\text{eff}_{DEA},y}$	0.0498***	0.0528***	0.0313***	0.0975***	0.00422	-0.0295***	-0.0173***	0.00251	-0.0781***
$MA^1_{\pi-\text{eff}_{DEA},p}$	0.0686***	0.0761***	0.0426***	0.0801***	-0.0163***	-0.0220***	-0.0294***	0.00246	-0.0636***
$MA^2_{\pi-\text{eff}_{DEA},y}$	0.0467***	0.0489***	0.0274***	0.0935***	0.00512	-0.0235***	-0.0188***	0.00289	-0.0754***
$MA^2_{\pi-\text{eff}_{DEA},p}$	0.0651***	0.0711***	0.0379***	0.0760***	-0.0148***	-0.0159***	-0.0306***	0.00290	-0.0605***
$MA^3_{\pi-\text{eff}_{DEA},y}$	0.0518***	0.0651***	0.0473***	0.1100***	-0.00652**	-0.0581***	-0.0225***	0.00413	-0.0869***
$MA^3_{\pi-\text{eff}_{DEA},p}$	0.0662***	0.0800***	0.0542***	0.0935***	-0.0235***	-0.0517***	-0.0309***	0.00442	-0.0725***

Since univariate correlations ignore extraneous influences on profitability, I also conduct multivariate regression analyses to further validate the MA proxies. Specifically, as in the main analysis, I regress ROA and ROE on managerial ability along with the first order lag of MA and control variables. This specification follows:

$$PM_{j,i,t} = \alpha + \sum_{k=0}^{1} \beta_{k+1} MA^{r}_{m,s,i,t-k} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{C.2}$$

where $PM_j \in \{ROA, ROE\}$ signifies the jth performance measure. $MA^{r}_{m,s}$ denotes the managerial ability measure, which has been computed over sample s (pooled vs yearly), using the set of regressors $r = 1, \ldots, 3$ based on method m, with $m \in \{\tau - \text{eff}_{DEA}, \tau - \text{eff}_{SFA}, \tau - \text{eff}_{GFA}, \pi - \text{eff}_{DEA}\}$. d_t are year dummies and $\mathbf{z}$ is a vector containing control variables. The control variables include the log of gross total assets to capture scale effects, cost efficiency parametrized by SFA as well as bank holding company status indicators and bank demographic variables as defined above. Table C.4 displays the results. These are organized in panels according to the efficiency parametrization method used to obtain managerial ability. Each panel, A-D, uses a different efficiency metric as basis for MA. Then each subpanel, A1, A2 etc. conducts the first stage Tobit regressions either on a pooled sample ($s = p$) or on a yearly sample ($s = y$). Finally, each set of two columns represents one of the three choices of first stage regressors, $r = 1, \ldots, 3$. For brevity, I report only the coefficients on MA and lagged MA. From Panel A it becomes apparent that the DEA revenue efficiency-based measure displays positive correlations with all performance metrics at lag 1. Contemporaneous instances are usually negative. Panel B indicates that SFA-based MA carries strong explanatory power in terms of performance, both contemporaneously and lagged. Panel C shows that the yearly Tobit regressions provide a GFA-based MA measure that is also positively and significantly associated with profitability, as long as the first stage Tobit regressors are either $r = 1$ or $r = 2$. For $r = 3$ and the pooled Tobit regressions, contemporaneous MA becomes significantly negative and insignificant at lag 1. Finally, Panel D shows that MA derived from DEA profit efficiency has the expected positive and significant association with profitability regardless of sample ($s = y, p$) or first stage regressors ($r = 1, \ldots, 3$). Overall, this evidence confirms that the MA measures behave as expected with respect to profitability, which validates the MA specifications.

Table C.4.: Bank Profitability and Managerial Ability.

This table reports results from fixed effects regressions of return on assets (ROA) and return on equity (ROE) on managerial ability (MA), lagged managerial ability and controls with bank and time fixed effects and standard errors clustered by bank. The dependent variable is intermediation quality. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are suppressed but include the log of gross total assets ($BKSIZE$), cost efficiency (CE) and bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau-$ eff represents revenue efficiency, while $\pi-$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A: $m = \tau - \text{eff}_{DEA}$											
	Panel A1: Yearly Tobit ($s = y$)						**Panel A2:** Pooled Tobit ($s = p$)					
	$r = 1$		$r = 2$		$r = 3$		$r = 1$		$r = 2$		$r = 3$	
	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE
$MA^r_{m,s,t}$	-0.00209***	-0.0446***	-0.00197***	-0.0431***	-0.00518***	-0.0770***	-0.00272***	-0.0563***	-0.00261***	-0.0553***	-0.00555***	-0.0805***
	(-4.05)	(-6.30)	(-3.82)	(-6.14)	(-9.66)	(-9.51)	(-5.46)	(-8.08)	(-5.25)	(-7.99)	(-10.36)	(-9.93)
$MA^r_{m,s,t-1}$	0.00195***	0.0278***	0.00188***	0.0270***	0.00272***	0.0430***	0.00207***	0.0278***	0.00200***	0.0266***	0.00325***	0.0481***
	(4.21)	(4.92)	(4.03)	(4.77)	(6.00)	(7.55)	(4.70)	(5.16)	(4.55)	(4.96)	(7.29)	(8.56)
	Panel B: $m = \tau - \text{eff}_{SFA}$											
	Panel B1: Yearly Tobit ($s = y$)						**Panel B2:** Pooled Tobit ($s = p$)					
	$r = 1$		$r = 2$		$r = 3$		$r = 1$		$r = 2$		$r = 3$	
	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE
$MA^r_{m,s,t}$	0.00521***	0.0512***	0.00504***	0.0503***	0.00235***	0.0290***	0.00516***	0.0507***	0.00499***	0.0492***	0.00290***	0.0345***
	(10.56)	(8.74)	(10.23)	(8.60)	(4.90)	(5.12)	(10.48)	(8.69)	(10.15)	(8.47)	(5.97)	(6.02)
$MA^r_{m,s,t-1}$	0.00202***	0.0263***	0.00206***	0.0271***	0.00313***	0.0404***	0.00193***	0.0202***	0.00204***	0.0220***	0.00306***	0.0375***
	(4.84)	(5.10)	(4.94)	(5.24)	(7.65)	(7.94)	(4.69)	(3.97)	(4.95)	(4.32)	(7.40)	(7.32)
	Panel C: $m = \tau - \text{eff}_{GFA}$											
	Panel C1: Yearly Tobit ($s = y$)						**Panel C2:** Pooled Tobit ($s = p$)					
	$r = 1$		$r = 2$		$r = 3$		$r = 1$		$r = 2$		$r = 3$	
	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE
$MA^r_{m,s,t}$	0.00251***	0.0367***	0.00248***	0.0369***	-0.00215**	-0.0281**	-0.00336***	-0.0430***	-0.00341***	-0.0432***	-0.00482***	-0.0632***
	(2.70)	(3.19)	(2.66)	(3.20)	(-2.31)	(-2.50)	(-3.62)	(-3.94)	(-3.67)	(-3.96)	(-5.20)	(-5.77)
$MA^r_{m,s,t-1}$	0.00238***	0.0330***	0.00248***	0.0344***	0.000983	0.0128	-0.000390	-0.00913	-0.000357	-0.00848	-0.000196	-0.00102
	(2.62)	(2.96)	(2.72)	(3.09)	(1.13)	(1.22)	(-0.46)	(-0.90)	(-0.42)	(-0.83)	(-0.23)	(-0.10)
	Panel D: $m = \pi - \text{eff}_{DEA}$											
	Panel D1: Yearly Tobit ($s = y$)						**Panel D2:** Pooled Tobit ($s = p$)					
	$r = 1$		$r = 2$		$r = 3$		$r = 1$		$r = 2$		$r = 3$	
	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE	ROA	ROE
$MA^r_{m,s,t}$	0.00138***	0.0226***	0.00140***	0.0234***	0.00191***	0.0342***	0.00181***	0.0300***	0.00179***	0.0300***	0.00190***	0.0336***
	(3.03)	(2.81)	(3.10)	(2.99)	(5.03)	(5.56)	(4.75)	(4.63)	(4.67)	(4.63)	(5.04)	(5.52)
$MA^r_{m,s,t-1}$	0.000347	0.00345	0.000362	0.00442	0.0000846	0.00576	0.000147	0.00650	0.000191	0.00726	0.000591	0.0124**
	(0.78)	(0.62)	(0.81)	(0.79)	(0.20)	(1.04)	(0.35)	(1.17)	(0.45)	(1.29)	(1.31)	(2.03)

C.1.3. Managerial Ability, Liquidity Creation and Risk-Taking

This section assesses the robustness of the main findings regarding liquidity creation, risk and managerial ability. Specifically, it investigates the impact of different managerial ability parametrizations on the outcome of the hypothesis tests. It also considers the impact that the choice of liquidity creation metric has on the findings.

C.1.3.1. Summary Statistics

Table C.5 reports summary statistics for the variables that play a role in the robustness checks and additional analyses. Thus it considers all the various parametrizations of managerial ability as well as two additional measures of liquidity creation: Berger and Bouwman's (2009) $CATNONFAT$ measure which excludes off-balance-sheet-items and Deep and Schaefer's (2004) LTG, the liquidity transformation gap, which is defined as the difference between short term assets and short term liabilities scaled by total assets.

Interestingly, the table shows that there is some substantial variation in the measures of managerial ability. Thus, for example, SFA and GFA-based MA for medium banks is lower than for other banks, while DEA revenue and profit efficiency-based MA mostly points to higher managerial ability for these banks. Furthermore, DEA suggests that small banks have low managerial ability and medium and large banks have greater managerial ability. Interestingly, average MA based on DEA profit efficiency is systematically larger than the other MA parametrizations although still close to zero. This suggests that profit efficiency may be harder to explain by the first stage Tobit regressions than the other efficiency measures. The additional liquidity creation indicators show, in keeping with Berger and Bouwman (2009), that including off-balance-sheet items yields substantially greater liquidity creation on average ($CATFAT > CATNONFAT$). Also, the liquidity transformation gap of Deep and Schaefer (2004), LTG, confirms that large banks tend to produce more liquidity per unit of assets. However, this measure understandably indicates a lower total level of liquidity creation than that of Berger and Bouwman (2009) since it is based on a more narrow conception of how liquidity is created.

Table C.5.: Summary Statistics.

$MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables all together and substitutes bank demographic variables. $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. $CATFAT$ ($CATNONFAT$) are the liquidity creation measures of Berger and Bouwman (2009) including (excluding) off-balance-sheet items. LTG is the liquidity transformation gap of Deep and Schaefer (2004).

	Panel A: Small Banks		*Panel B: Medium Banks*		*Panel C: Large Banks*		*Panel D: All Banks*	
Parameter	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)
$MA^1_{\tau-\text{eff}_{DEA},p}$	-0.0033062	0.0911256	0.0128553	0.1093815	0.0613018	0.1242834	-0.0012608	0.093266
$MA^1_{\tau-\text{eff}_{DEA},y}$	-0.0033818	0.0896094	0.0139924	0.1071375	0.0617406	0.1215685	-0.0012795	0.0917093
$MA^2_{\tau-\text{eff}_{DEA},p}$	-0.0032531	0.0909663	0.0125202	0.1087806	0.0593858	0.1237022	-0.0012661	0.0930448
$MA^2_{\tau-\text{eff}_{DEA},y}$	-0.0033321	0.0893405	0.0136914	0.1061675	0.0599401	0.1208346	-0.0012842	0.0913681
$MA^3_{\tau-\text{eff}_{DEA},p}$	-0.002199	0.092674	0.0007043	0.11066	0.0365512	0.1278668	-0.0012267	0.0945035
$MA^3_{\tau-\text{eff}_{DEA},y}$	-0.0022305	0.0919705	0.001701	0.109038	0.0360524	0.1254116	-0.0012302	0.0937069
$MA^1_{\tau-\text{eff}_{SFA},p}$	0.0206532	0.157387	-0.2908927	0.1567957	-0.3502813	0.2150109	0.0007185	0.1776112
$MA^1_{\tau-\text{eff}_{SFA},y}$	0.0206202	0.1567522	-0.2918914	0.1556805	-0.3472055	0.218889	0.0007187	0.1770744
$MA^2_{\tau-\text{eff}_{SFA},p}$	0.0205153	0.1569016	-0.2901324	0.1576046	-0.3470011	0.216859	0.0006904	0.1770784
$MA^2_{\tau-\text{eff}_{SFA},y}$	0.0204854	0.1562805	-0.291051	0.1566113	-0.3448219	0.2208466	0.0006764	0.1765965
$MA^3_{\tau-\text{eff}_{SFA},p}$	0.0161772	0.1678165	-0.2371879	0.1561606	-0.2662571	0.2332872	0.000397	0.1803818
$MA^3_{\tau-\text{eff}_{SFA},y}$	0.0161227	0.1668732	-0.237121	0.1560959	-0.2655502	0.2344871	0.0003641	0.1795586
$MA^1_{\tau-\text{eff}_{GFA},p}$	0.0026846	0.0325162	-0.0804364	0.0942167	0.0058693	0.1179411	-0.0003569	0.0434291
$MA^1_{\tau-\text{eff}_{GFA},y}$	0.0026847	0.028723	-0.0818564	0.0776813	0.0065008	0.0969937	-0.0003959	0.0383368
$MA^2_{\tau-\text{eff}_{GFA},p}$	0.0026829	0.0325053	-0.0804055	0.0941917	0.0059479	0.1179693	-0.0003556	0.0434191
$MA^2_{\tau-\text{eff}_{GFA},y}$	0.0026804	0.0286917	-0.0818081	0.0775588	0.0064984	0.0969146	-0.0003981	0.0382969
$MA^3_{\tau-\text{eff}_{GFA},p}$	0.0055237	0.0354758	-0.1127575	0.0953325	-0.0463332	0.1222073	-0.0000604	0.0490793
$MA^3_{\tau-\text{eff}_{GFA},y}$	0.0055147	0.0349136	-0.1128006	0.089955	-0.0459499	0.1152744	-0.0000619	0.0479278
$MA^1_{\pi-\text{eff}_{DEA},p}$	0.002579	0.0703746	-0.0009013	0.0937166	0.0528695	0.12649	0.0035698	0.0734703
$MA^1_{\pi-\text{eff}_{DEA},y}$	0.0051537	0.0691925	0.0041217	0.0937322	0.0560356	0.1296798	0.0062493	0.0725381
$MA^2_{\pi-\text{eff}_{DEA},p}$	0.0026411	0.0700982	-0.0011304	0.0923145	0.0506548	0.1253829	0.0035702	0.0730795
$MA^2_{\pi-\text{eff}_{DEA},y}$	0.0052113	0.069005	0.0038826	0.0924238	0.0541793	0.1284803	0.0062532	0.0722308
$MA^3_{\pi-\text{eff}_{DEA},p}$	0.000961	0.0694954	0.0288065	0.0895305	0.0862896	0.1221502	0.0039052	0.0731859
$MA^3_{\pi-\text{eff}_{DEA},y}$	0.0035262	0.0685336	0.0340639	0.0893787	0.0900904	0.1237163	0.0065986	0.0724484
$CATFAT$	0.2609532	0.1704291	0.3772222	0.162688	0.4006081	0.1750225	0.26842	0.1728281
$CATNONFAT$	0.2116481	0.1478937	0.2833484	0.1351756	0.2576988	0.1359127	0.2153595	0.1479445
LTG	0.0814323	0.1665111	0.1423029	0.158554	0.1140028	0.179544	0.0844377	0.1669803
N	94944		3781		2251		100976	

C.1.3.2. Managerial Ability and Liquidity Creation

As in the main analysis, the first step is concerned with the relation that holds between liquidity creation and managerial ability, which is encapsulated in hypothesis A1. If this hypothesis holds, one would expect managerial ability to exert a positive influence on liquidity creation. Again this analysis uses the following specification:

$$\frac{LC_{j,i,t}}{GTA_{i,t}} = \alpha + \beta_1 MA^r_{m,s,i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}. \tag{C.3}$$

LC is a liquidity creation measure with $LC \in \{CATFAT, CATNONFAT, LTG\}$ indexed by j and GTA representing gross total assets. All controls and other regressors are as previously defined.

First, Tables C.6-C.9 report the results for the $CATFAT$ and $CATNONFAT$ measures of liquidity creation. The results for $CATFAT$ show that the findings are quite robust to a) the parametrization of efficiency, b) choice of first stage regressors and c) pooled vs. yearly Tobit regressions. Specifically for this set of regressors ($r = 1$), DEA revenue efficiency-based MA confirms the positive relation between MA and $CATFAT$ liquidity creation for small banks and the full sample. This last result holds regardless of first stage regressors (Panel A), which suggests robustness to the efficiency parametrization method. Furthermore, the results in Panel B show that, given that SFA is used to obtain revenue efficiency, the findings do not depend on the choice of first stage regressors; coefficients on managerial ability are significantly positive for small and large banks as well as the full sample. In addition, Panel D shows that, when DEA-based profit efficiency is used to parametrize MA as in the main analysis, a robust and significantly positive relation between MA and $CATFAT$ obtains for medium sized banks. Coefficients in Panel C are insignificant. The only coefficients that speak against this reading of the results are the small bank and full sample coefficients for Panel D with $r = 3$. Hence the bulk of the evidence confirms the findings in the main analysis.

Moreover, these findings are emphatically supported by results obtained for a pooled Tobit regression approach, which is reported in Table C.7. This provides an additional confirmation of the previous findings.

Next, I consider how results change, if off-balance-sheet items are omitted from the definition of liquidity creation by investigating the $CATNONFAT$ measure. Results are tabulated in Tables C.8-C.9. Let the base case again be Panel D, $r = 1$ in Table C.8. As in the main analysis using $CATFAT$ the coefficients indicate that more ably managed banks create greater liquidity. This result is significant for small banks.

Table C.6.: *CATFAT* Liquidity Creation and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) *CATFAT* measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0395***	0.00745	0.0219	0.0334***	0.0393***	0.00779	0.0264	0.0335***	0.0364***	0.00664	0.0324	0.0329***
	(6.30)	(0.29)	(0.57)	(5.48)	(6.26)	(0.30)	(0.68)	(5.48)	(6.26)	(0.27)	(0.81)	(5.74)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0766***	0.0178*	0.0232**	0.0614***	0.0772***	0.0177*	0.0231**	0.0620***	0.0783***	0.0183*	0.0213**	0.0620***
	(13.23)	(1.65)	(2.08)	(12.99)	(13.39)	(1.65)	(2.08)	(13.17)	(14.03)	(1.72)	(2.01)	(13.53)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0558***	-0.00268	-0.00265	0.0413***	0.0555***	-0.00296	-0.00264	0.0413***	0.0328***	-0.00318	0.00498	0.0302***
	(4.28)	(-0.15)	(-0.10)	(4.17)	(4.25)	(-0.16)	(-0.10)	(4.16)	(2.89)	(-0.18)	(0.22)	(3.55)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0136**	0.0511**	-0.0220	0.0114*	0.0136**	0.0507**	-0.0195	0.0116*	-0.0110*	0.0498**	-0.0315	-0.0117*
	(1.99)	(2.27)	(-0.64)	(1.69)	(2.00)	(2.23)	(-0.57)	(1.72)	(-1.69)	(2.20)	(-0.97)	(-1.83)

Table C.7.: $CATFAT$ Liquidity Creation and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0290***	0.00369	0.0371	0.0271***	0.0285***	0.00453	0.0371	0.0266***	0.0335***	0.00463	0.0310	0.0310***
	(4.89)	(0.15)	(0.96)	(4.69)	(4.80)	(0.18)	(0.95)	(4.59)	(5.78)	(0.19)	(0.80)	(5.46)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0762***	0.0163	0.0224**	0.0606***	0.0772***	0.0162	0.0223**	0.0614***	0.0805***	0.0173	0.0209**	0.0626***
	(13.22)	(1.50)	(1.98)	(12.80)	(13.44)	(1.50)	(1.98)	(13.02)	(14.18)	(1.59)	(1.97)	(13.49)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.00756	-0.00194	0.0110	0.0115	-0.00710	-0.00199	0.0108	0.0117	-0.00288	-0.00175	0.00552	0.0134
	(-0.67)	(-0.11)	(0.45)	(1.38)	(-0.63)	(-0.11)	(0.44)	(1.41)	(-0.26)	(-0.10)	(0.25)	(1.63)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.00741	0.0470**	-0.0201	0.00697	0.00709	0.0468**	-0.0191	0.00666	-0.0121*	0.0446**	-0.0304	-0.0124**
	(1.12)	(2.07)	(-0.58)	(1.07)	(1.08)	(2.05)	(-0.55)	(1.03)	(-1.89)	(1.97)	(-0.93)	(-1.99)

When SFA revenue efficiency is used to parametrize MA results also support the main analysis Concretely, small and large banks as well as the full sample report significant coefficients. This holds regardless of regressors ($r = 1, \ldots, 3$ within Panel B). Furthermore, Panel A again shows supporting evidence from DEA revenue efficiency, which is qualitatively similar to the $CATFAT$ case. In addition, GFA also supports the findings with significantly positive coefficients for small banks and the full sample (Panel C, $r = 1, \ldots, 3$). What is more, none of these findings are driven by running yearly Tobit regressions vis-á-vis pooled ones as can be seen from Table C.9, which reaffirms the earlier findings.

The third step is to consider how results change if the Berger and Bouwman method for defining liquidity creation is abandoned all together. To this end I analyze results obtained using the liquidity transformation gap of Deep and Schaefer (2004) scaled by total assets as dependent variable. These results are reported in Tables C.10-C.11.

Again, consider as the base case Table C.10, Panel D, $r = 1$. This provides very strong support for the main analysis. Specifically, MA is strongly significantly positively related to liquidity creation regardless of first stage regressors ($r = 1, \ldots, 3$) for small and medium banks and the full sample. Results for SFA-based revenue efficiency in panel B are somewhat weaker than for $CATFAT$ and $CATNONFAT$ but still qualitatively surprisingly similar. Concretely, all coefficients on MA are positive and, for small banks and the pooled sample, also significant. This finding is not driven by the selection of first stage regressors (Panel B, $r = 1, \ldots, 3$). Nor is this finding driven by the efficiency parametrization method used to obtain managerial ability. Thus, DEA and GFA revenue efficiency both confirm the positive and frequently significant impact that MA has on liquidity creation as proxied by LTG (Panels A, C). Interestingly, DEA revenue efficiency-based MA is more sensitive to effects that obtain for medium banks, while GFA seems to be picking up more large bank effects. Again, results are independent of the set of first stage regressors. Finally, these results prove robust to the use of pooled or yearly Tobit regressions in obtaining MA, as Table C.11 indicates. The only change is that the GFA-based gain additional significance for large banks.

To sum up, the analysis of various specifications of liquidity creation and managerial ability shows that the relation between these two facets of bank behavior is robustly and significantly positive during normal times. This provides strong support for the acceptance of A1, as advocated in the main analysis.

Table C.8.: $CATNONFAT$ Liquidity Creation and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A: $m = \tau - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0362***	-0.0103	-0.00320	0.0286***	0.0361***	-0.0111	-0.000739	0.0286***	0.0364***	-0.00747	0.000424	0.0314***
	(6.43)	(-0.41)	(-0.11)	(5.20)	(6.39)	(-0.43)	(-0.02)	(5.18)	(6.94)	(-0.30)	(0.01)	(6.10)
	Panel B: $m = \tau - \text{eff}_{SFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0631***	0.00267	0.0171*	0.0514***	0.0640***	0.00292	0.0173*	0.0521***	0.0675***	0.00476	0.0167*	0.0539***
	(12.52)	(0.29)	(1.87)	(12.34)	(12.73)	(0.32)	(1.90)	(12.56)	(13.84)	(0.54)	(1.94)	(13.30)
	Panel C: $m = \tau - \text{eff}_{GFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0668***	-0.0159	0.0144	0.0469***	0.0666***	-0.0162	0.0147	0.0469***	0.0503***	-0.0146	0.0162	0.0456***
	(5.87)	(-1.04)	(0.66)	(5.42)	(5.84)	(-1.06)	(0.68)	(5.41)	(5.04)	(-0.99)	(0.83)	(6.02)
	Panel D: $m = \pi - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0139**	0.0249	-0.0514	0.00831	0.0144**	0.0236	-0.0488	0.00873	-0.00590	0.0325	-0.0535*	-0.00919
	(2.28)	(1.07)	(-1.58)	(1.36)	(2.36)	(1.01)	(-1.51)	(1.43)	(-1.02)	(1.52)	(-1.70)	(-1.58)

Table C.9.: $CATNONFAT$ Liquidity Creation and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0275***	-0.0133	0.00514	0.0243***	0.0269***	-0.0137	0.00512	0.0236***	0.0331***	-0.00916	0.00163	0.0293***
	(5.15)	(-0.54)	(0.18)	(4.66)	(5.04)	(-0.55)	(0.18)	(4.54)	(6.33)	(-0.39)	(0.06)	(5.73)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0630***	0.00111	0.0163*	0.0506***	0.0641***	0.00133	0.0165*	0.0515***	0.0687***	0.00352	0.0161*	0.0538***
	(12.58)	(0.12)	(1.78)	(12.09)	(12.83)	(0.14)	(1.81)	(12.35)	(13.89)	(0.39)	(1.88)	(13.10)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0242**	-0.0139	0.0223	0.0353***	0.0247**	-0.0139	0.0221	0.0355***	0.0291***	-0.0125	0.0169	0.0370***
	(2.45)	(-0.94)	(1.06)	(4.75)	(2.50)	(-0.94)	(1.06)	(4.79)	(2.96)	(-0.84)	(0.86)	(5.04)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0109*	0.0283	-0.0519	0.00842	0.0107*	0.0273	-0.0506	0.00810	-0.00501	0.0293	-0.0541*	-0.00719
	(1.85)	(1.22)	(-1.58)	(1.42)	(1.81)	(1.18)	(-1.53)	(1.37)	(-0.88)	(1.38)	(-1.72)	(-1.26)

Table C.10.: LTG Liquidity Creation and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of Deep and Schaefer's (2004) liquidity transformation gap (LTG) measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau-$ eff represents revenue efficiency, while $\pi-$eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.174***	0.0995***	0.0549	0.157***	0.174***	0.0993***	0.0553	0.157***	0.158***	0.0952***	0.0460	0.149***
	(22.29)	(2.93)	(1.19)	(19.97)	(22.32)	(2.89)	(1.19)	(19.99)	(21.52)	(2.76)	(0.97)	(20.23)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0752***	0.0141	0.0164	0.0643***	0.0773***	0.0143	0.0172	0.0658***	0.0767***	0.0156	0.0172	0.0631***
	(10.67)	(0.94)	(1.10)	(10.59)	(10.99)	(0.95)	(1.15)	(10.86)	(11.18)	(1.05)	(1.21)	(10.61)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.119***	0.0121	0.0444	0.0802***	0.121***	0.0118	0.0443	0.0810***	0.123***	0.00941	0.0522*	0.105***
	(7.12)	(0.45)	(1.46)	(6.00)	(7.18)	(0.44)	(1.45)	(6.05)	(8.63)	(0.36)	(1.94)	(9.34)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0845***	0.126***	0.00326	0.0729***	0.0864***	0.126***	0.00382	0.0748***	0.0336***	0.120***	-0.0236	0.0264***
	(10.21)	(4.37)	(0.08)	(8.67)	(10.44)	(4.29)	(0.09)	(8.92)	(4.16)	(3.86)	(-0.56)	(3.24)

Table C.11.: LTG Liquidity Creation and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of Deep and Schaefer's (2004) liquidity transformation gap (LTG) measure of liquidity creation scaled by total assets on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
Panel A: $m = \tau - \text{eff}_{DEA}$												
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.160***	0.0914***	0.0596	0.153***	0.159***	0.0910***	0.0575	0.152***	0.159***	0.0906***	0.0482	0.152***
	(21.52)	(2.69)	(1.28)	(20.66)	(21.39)	(2.69)	(1.24)	(20.51)	(21.78)	(2.71)	(1.04)	(20.89)
Panel B: $m = \tau - \text{eff}_{SFA}$												
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0676***	0.0138	0.0158	0.0554***	0.0695***	0.0140	0.0163	0.0571***	0.0713***	0.0160	0.0164	0.0574***
	(9.65)	(0.91)	(1.05)	(9.14)	(9.96)	(0.93)	(1.09)	(9.43)	(10.24)	(1.07)	(1.15)	(9.53)
Panel C: $m = \tau - \text{eff}_{GFA}$												
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.105***	0.0145	0.0543*	0.104***	0.106***	0.0145	0.0543*	0.104***	0.111***	0.0141	0.0515*	0.106***
	(7.48)	(0.55)	(1.83)	(9.52)	(7.55)	(0.55)	(1.83)	(9.57)	(7.93)	(0.53)	(1.89)	(9.75)
Panel D: $m = \pi - \text{eff}_{DEA}$												
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0870***	0.125***	-0.00112	0.0842***	0.0870***	0.123***	-0.00149	0.0839***	0.0519***	0.112***	-0.0235	0.0479***
	(10.83)	(4.29)	(-0.03)	(10.42)	(10.85)	(4.20)	(-0.03)	(10.41)	(6.58)	(3.70)	(-0.55)	(6.06)

C.1.3.3. Managerial Ability and Bank Risk-Taking

Following the logic of the main analysis, the next step is to investigate the robustness of findings regarding bank risk and managerial ability as formalized in hypothesis A2. This is accomplished by replicating the risk regressions for all permutations of the MA specification. If the main results hold, one would expect positive associations between MA and NPL and negative associations between MA and $T1R$ and $LAGTA$. To test this conjecture, this section runs regressions of the form

$$KRI_{k,i,t} = \alpha + \beta_1 MA^r_{m,s,i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{14} \theta_t d_t + \upsilon_i + \epsilon_{i,t}. \tag{C.4}$$

Here KRI_k represents the key risk indicator with $k \in \{NPL, T1R, LAGTA\}$. All other regressors and controls are as previously defined. Results are reported in Tables C.12-C.17.

Table C.12, Panel D for $r = 1$ replicates the basic findings regarding nonperforming loans (NPL). Thus the main analysis tentatively suggests that more able managers favor a less risky bank strategy, which induces a lower level of nonperforming loans. Panel D, $r = 1, \ldots, 3$ shows that this result does not depend on the set of regressors used to obtain MA. Evidence from the other methods (Panels A-C) is limited. However it does seem that the majority of the evidence indicates that more able managers prefer greater levels of nonperforming loans and thus more risky bank operations. Specifically, the results for GFA confirm this finding for small banks and the full sample (Panel C). Furthermore, DEA and SFA-revenue efficiency also provide support for this conclusion in Panels A and B. This would be consistent with the fact that the other risk indicators ($LAGTA$ and $T1R$) indicate that more able managers prefer to take on greater risk. This is supported by the pooled Tobit regressions in Table C.13.

I proceed in a similar manner to validate the robustness of findings regarding capitalization. The dependent variable here is the tier 1 ratio ($T1R$) and Tables C.14-C.15 report the results. The initial analysis shows that more ably managed banks are also more thinly capitalized (Table C.14, Panel D, $r = 1$). Further analysis shows, that, as in the main investigation this result holds across all sets of first stage regressors (Panel D, $r = 1, \ldots, 3$). Specifically, the full sample additionally shows a significantly negative coefficient when $r = 2, 3$. Similar results obtain for SFA revenue efficiency in panel B with the exception of medium banks where significantly positive coefficients obtain for medium banks for $r = 1, 2$. Medium banks may need to hold greater amounts of tier 1 capital because they neither have access to wholesale funding markets nor are

Table C.12.: Nonperforming Loans (NPL) and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of the ratio of nonperforming loans over total loans (NPL) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A: $m = \tau - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.000254	0.00229	0.00504	-0.00000120	-0.000313	0.00240	0.00488	-0.0000613	0.00272***	0.00403	0.00308	0.00325***
	(-0.26)	(0.79)	(0.98)	(-0.00)	(-0.32)	(0.83)	(0.95)	(-0.07)	(2.90)	(1.29)	(0.64)	(3.63)
	Panel B: $m = \tau - \text{eff}_{SFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.000794	-0.000546	0.00286*	0.00125	0.000818	-0.000502	0.00286*	0.00127	0.00241**	-0.00000497	0.00300*	0.00250***
	(0.80)	(-0.28)	(1.65)	(1.55)	(0.83)	(-0.26)	(1.67)	(1.59)	(2.53)	(-0.00)	(1.78)	(3.20)
	Panel C: $m = \tau - \text{eff}_{GFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.00490*	-0.00475	-0.000534	0.000691	0.00463*	-0.00482	-0.000528	0.000553	0.0149***	-0.00548*	0.000725	0.0105***
	(1.89)	(-1.57)	(-0.15)	(0.40)	(1.78)	(-1.59)	(-0.14)	(0.32)	(6.72)	(-1.83)	(0.24)	(6.97)
	Panel D: $m = \pi - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.000911	-0.0123***	-0.00311	-0.00146	-0.000840	-0.0122***	-0.00355	-0.00140	0.00258**	-0.00782**	-0.00316	0.00217**
	(-0.81)	(-3.12)	(-0.54)	(-1.35)	(-0.74)	(-3.13)	(-0.62)	(-1.30)	(2.36)	(-2.10)	(-0.55)	(2.05)

Table C.13.: Nonperforming Loans (NPL) and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of the ratio of nonperforming loans over total loans (NPL) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.000649	0.00203	0.00291	0.00122	0.000606	0.00194	0.00283	0.00117	0.00164*	0.00333	0.00322	0.00226***
	(0.69)	(0.68)	(0.60)	(1.36)	(0.65)	(0.65)	(0.59)	(1.31)	(1.78)	(1.09)	(0.67)	(2.58)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.00165*	-0.000436	0.00299*	0.00184**	0.00171*	-0.000387	0.00302*	0.00189**	0.00264***	0.000202	0.00324*	0.00258***
	(1.68)	(-0.23)	(1.68)	(2.29)	(1.75)	(-0.20)	(1.71)	(2.36)	(2.74)	(0.10)	(1.89)	(3.28)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.0295***	-0.00450	0.000859	0.0194***	0.0295***	-0.00446	0.000865	0.0194***	0.0297***	-0.00486	0.000148	0.0189***
	(13.93)	(-1.50)	(0.24)	(13.31)	(13.95)	(-1.49)	(0.24)	(13.33)	(14.19)	(-1.61)	(0.05)	(13.23)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.000490	-0.0107***	-0.00260	-0.000520	-0.000407	-0.0103***	-0.00282	-0.000435	0.00132	-0.00748**	-0.00227	0.00139
	(-0.45)	(-2.71)	(-0.46)	(-0.49)	(-0.37)	(-2.66)	(-0.49)	(-0.41)	(1.23)	(-2.07)	(-0.38)	(1.34)

they firmly rooted in local deposit markets. Moreover, support for this reading comes from the GFA method in Panel C ($r = 3$) and from DEA revenue efficiency in Panel A ($r = 3$). Transitioning from yearly to pooled Tobit regressions in Table C.15 does not qualitatively affect results.

Finally, Tables C.16-C.17 replicate the same procedure for the analysis of $LAGTA$. Initial findings suggest that more ably managed banks tended to hold lower levels of liquid assets per unit of assets (Table C.16 Panel D, $r = 1$). These findings are very robust. Specifically, neither the choice of first stage Tobit regressors ($r = 1, \ldots, 3$) nor the base efficiency used to parametrize MA ($\tau - \text{eff}_{DEA}$, $\tau - \text{eff}_{SFA}$, $\tau - \text{eff}_{GFA}$, $\pi - \text{eff}_{DEA}$) weakens this finding: all parametrizations show significantly negative coefficients for small banks and the full sample. In addition, for GFA, significantly negative coefficients obtain also for large banks and (Panels C). Moreover, these results are strongly confirmed by Table C.17, i.e. by MA based on pooled Tobit regressions. Hence the finding of more managerial ability being associated with less liquid banks is robust.

The main analysis concludes that more able managers tend to run somewhat more risky banks. Overall, this section has offered substantial evidence that the initial conclusion is robust to the type of MA parametrization that is used. Although this robustness is not as strong as that of the liquidity creation results, it still suggests that the initial reading is justified: more ably managed banks are riskier in normal times and hypothesis A2 ought to be accepted.

Table C.14.: Tier 1 Ratio ($T1R$) and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of the ratio of tier 1 capital over total assets ($T1R$) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.00471*	0.00367	0.00415	0.00722***	0.00461*	0.00377	0.00402	0.00714***	-0.0135***	-0.00481	-0.00499	-0.0116***
	(1.71)	(0.32)	(0.47)	(2.75)	(1.67)	(0.32)	(0.45)	(2.71)	(-5.26)	(-0.47)	(-0.55)	(-4.72)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.00883***	0.00883**	-0.00153	-0.0102***	-0.0106***	0.00863**	-0.00160	-0.0114***	-0.0280***	0.00482	-0.00244	-0.0234***
	(-3.70)	(2.07)	(-0.57)	(-5.23)	(-4.42)	(2.05)	(-0.61)	(-5.85)	(-12.06)	(1.17)	(-0.94)	(-12.37)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0287***	0.0201**	0.00106	-0.0144***	-0.0301***	0.0201**	0.00113	-0.0152***	-0.0140***	0.0179**	-0.000861	-0.00646*
	(-5.07)	(2.45)	(0.16)	(-3.56)	(-5.30)	(2.46)	(0.17)	(-3.73)	(-2.94)	(2.34)	(-0.15)	(-1.88)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.00845***	0.0166	0.00811	-0.00316	-0.0106***	0.0159	0.00726	-0.00530**	-0.0240***	0.00981	0.00716	-0.0181***
	(-3.08)	(1.53)	(1.18)	(-1.23)	(-3.86)	(1.48)	(1.07)	(-2.06)	(-8.97)	(1.00)	(0.94)	(-7.23)

Table C.15.: Tier 1 Ratio ($T1R$) and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of the ratio of tier 1 capital over total assets ($T1R$) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	0.00587**	0.00444	0.00251	0.00697***	0.00675***	0.00495	0.00276	0.00784***	-0.0132***	-0.00505	-0.00430	-0.0117***
	(2.25)	(0.41)	(0.30)	(2.80)	(2.58)	(0.46)	(0.32)	(3.15)	(-5.21)	(-0.51)	(-0.49)	(-4.85)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.00335	0.00921**	-0.00143	-0.00591***	-0.00522**	0.00903**	-0.00160	-0.00726***	-0.0238***	0.00533	-0.00233	-0.0204***
	(-1.41)	(2.10)	(-0.54)	(-3.04)	(-2.20)	(2.05)	(-0.62)	(-3.74)	(-10.22)	(1.21)	(-0.92)	(-10.80)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.000118	0.0202***	0.00106	0.00156	-0.00125	0.0201**	0.000979	0.000929	-0.0136***	0.0194**	-0.000812	-0.00599*
	(-0.03)	(2.59)	(0.16)	(0.46)	(-0.27)	(2.58)	(0.15)	(0.28)	(-2.87)	(2.52)	(-0.13)	(-1.79)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0184***	0.0134	0.00688	-0.0133***	-0.0193***	0.0132	0.00620	-0.0142***	-0.0250***	0.00810	0.00582	-0.0198***
	(-6.80)	(1.26)	(1.04)	(-5.25)	(-7.15)	(1.25)	(0.95)	(-5.60)	(-9.49)	(0.86)	(0.77)	(-7.99)

Table C.16.: Liquid Assets ($LAGTA$) and Managerial Ability, $s = y$.

This table reports results from fixed effects regressions of the ratio of liquid assets over total assets ($LAGTA$) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau-$ eff represents revenue efficiency, while $\pi-$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

					Panel A: $m = \tau - \text{eff}_{DEA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0468***	-0.0145	-0.0292	-0.0409***	-0.0483***	-0.0149	-0.0299	-0.0422***	-0.0489***	-0.0169	-0.0237	-0.0467***
	(-8.12)	(-0.62)	(-0.77)	(-7.24)	(-8.34)	(-0.63)	(-0.79)	(-7.44)	(-9.01)	(-0.72)	(-0.60)	(-8.73)
					Panel B: $m = \tau - \text{eff}_{SFA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.112***	0.0136	-0.00799	-0.0828***	-0.112***	0.0137	-0.00854	-0.0829***	-0.110***	0.0131	-0.0103	-0.0808***
	(-21.28)	(1.41)	(-0.83)	(-19.06)	(-21.38)	(1.43)	(-0.88)	(-19.15)	(-21.70)	(1.36)	(-1.10)	(-19.15)
					Panel C: $m = \tau - \text{eff}_{GFA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.112***	-0.00479	-0.0345	-0.0699***	-0.113***	-0.00427	-0.0344	-0.0703***	-0.0751***	-0.00194	-0.0422**	-0.0591***
	(-9.54)	(-0.28)	(-1.36)	(-7.92)	(-9.59)	(-0.25)	(-1.36)	(-7.96)	(-7.42)	(-0.12)	(-1.98)	(-7.81)
					Panel D: $m = \pi - \text{eff}_{DEA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0673***	-0.0379	0.0257	-0.0547***	-0.0682***	-0.0353	0.0263	-0.0557***	-0.0588***	-0.0525**	0.0476	-0.0496***
	(-10.59)	(-1.60)	(0.76)	(-8.77)	(-10.73)	(-1.48)	(0.78)	(-8.93)	(-9.63)	(-2.22)	(1.43)	(-8.26)

Table C.17.: Liquid Assets ($LAGTA$) and Managerial Ability, $s = p$.

This table reports results from fixed effects regressions of the ratio of liquid assets over total assets ($LAGTA$) on lagged managerial ability ($MA^r_{m,s,t-1}$) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	Panel A: $m = \tau - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0442***	-0.00911	-0.0266	-0.0429***	-0.0436***	-0.00903	-0.0254	-0.0423***	-0.0464***	-0.0114	-0.0229	-0.0456***
	(-8.04)	(-0.40)	(-0.69)	(-7.98)	(-7.95)	(-0.40)	(-0.66)	(-7.87)	(-8.61)	(-0.50)	(-0.59)	(-8.61)
	Panel B: $m = \tau - \text{eff}_{SFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.107***	0.0152	-0.00836	-0.0784***	-0.107***	0.0150	-0.00910	-0.0791***	-0.109***	0.0134	-0.0109	-0.0799***
	(-20.47)	(1.59)	(-0.86)	(-18.05)	(-20.68)	(1.58)	(-0.94)	(-18.27)	(-21.35)	(1.38)	(-1.16)	(-18.76)
	Panel C: $m = \tau - \text{eff}_{GFA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0764***	-0.00699	-0.0409*	-0.0629***	-0.0768***	-0.00698	-0.0408*	-0.0631***	-0.0747***	-0.00718	-0.0429**	-0.0618***
	(-7.60)	(-0.42)	(-1.70)	(-8.45)	(-7.64)	(-0.41)	(-1.69)	(-8.48)	(-7.48)	(-0.43)	(-2.00)	(-8.40)
	Panel D: $m = \pi - \text{eff}_{DEA}$											
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,t-1}$	-0.0716***	-0.0502**	0.0258	-0.0636***	-0.0715***	-0.0493**	0.0259	-0.0635***	-0.0590***	-0.0517**	0.0449	-0.0518***
	(-11.67)	(-2.08)	(0.73)	(-10.55)	(-11.67)	(-2.04)	(0.73)	(-10.54)	(-9.88)	(-2.22)	(1.34)	(-8.83)

C.1.4. Effects of Managerial Ability on Liquidity Creation and Risk-Taking During the Crisis

This section subjects the analysis of the financial crisis to additional validation by considering a variety of modifications to the base case. As in the preceding sections these modifications relate to the MA measure and to the indicators of bank liquidity creation.

C.1.4.1. Effects on Liquidity Creation

The main analysis of the financial crisis shows that more able management pre-crisis led banks to contract their liquidity creation activity more during the crisis, consistent with hypothesis A3b. Moreover, the main results show that the crisis itself exerted a negative effect on bank liquidity creation. This section now investigates the robustness of these findings to the parametrization of the managerial ability measure and to the choice of liquidity creation indicator. To do so, I run difference-in-differences regressions with bank fixed effects of the form

$$\frac{LC_{j,i,t}}{GTA_{i,t}} = \alpha + \beta_1 \delta_c + \beta_2 MA^r_{m,s,i,06} \times \delta_c + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}. \tag{C.5}$$

All variables are as previously defined and Tables C.19-C.22 report the results. If the main results are robust, one would expect to find significantly negative coefficients on δ_c and $MA^r_{m,s,06}$.

Indeed, the crisis dummy is significantly negative in the vast majority of cases and never significantly positive. Hence results related to this variable are not discussed further. In terms of the results regarding managerial ability, the first step is to consider the liquidity creation measures of Berger and Bouwman (2009), $CATFAT$ and $CATNONFAT$.

The findings for $CATFAT$ include the baseline specification in Table C.18, Panel D, $r = 1$. Panel D shows that the main results regarding MA are very robust to the selection of first stage Tobit regressors ($r = 1, \ldots, 3$). In addition, the SFA results in Panel B, with strongly significantly positive coefficients throughout, emphatically suggest that the initially insignificant coefficients are underestimating the actual effects. Moreover, the DEA results in Panel A for small banks and the full sample also confirm that more able pre-crisis management led banks to contract their liquidity creation more during the crisis. Only the GFA results in Panel C provide contrary evidence with a number of significantly positive coefficients. The picture does not change qualitatively if one uses pooled instead of yearly Tobit regressions to obtain MA, as can be seen from Table C.19. Thus, the majority of the evidence supports the main conclusion.

Table C.18.: $CATFAT$ Liquidity Creation and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0249**	-0.0314	-0.0671	-0.0310***	-0.0249**	-0.0291	-0.0681	-0.0310***	-0.0200**	-0.00510	-0.0294	-0.0210**
	(-2.53)	(-0.67)	(-0.85)	(-3.19)	(-2.54)	(-0.61)	(-0.85)	(-3.19)	(-2.28)	(-0.13)	(-0.37)	(-2.41)
δ_c	-0.00530***	-0.00772*	-0.0104	-0.00658***	-0.00530***	-0.00775*	-0.0104	-0.00658***	-0.00522***	-0.00810**	-0.0148**	-0.00657***
	(-6.30)	(-1.94)	(-1.45)	(-8.05)	(-6.30)	(-1.95)	(-1.46)	(-8.04)	(-6.20)	(-2.04)	(-2.37)	(-8.03)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0234***	-0.0669***	0.00360	-0.0123***	-0.0229***	-0.0667***	0.00366	-0.0119***	-0.0181***	-0.0700***	0.00491	-0.0125***
	(-4.92)	(-3.33)	(0.11)	(-3.24)	(-4.78)	(-3.34)	(0.11)	(-3.13)	(-4.03)	(-3.45)	(0.15)	(-3.24)
δ_c	-0.00465***	-0.0259***	-0.0140	-0.00661***	-0.00468***	-0.0258***	-0.0140	-0.00661***	-0.00495***	-0.0225***	-0.0140	-0.00664***
	(-5.45)	(-3.99)	(-0.79)	(-8.05)	(-5.48)	(-4.00)	(-0.79)	(-8.06)	(-5.84)	(-4.15)	(-0.98)	(-8.09)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.179***	0.230**	-0.0386	0.133***	0.184***	0.229**	-0.0376	0.135***	0.0323	0.160**	-0.0335	0.0632***
	(3.68)	(2.52)	(-0.51)	(4.69)	(3.77)	(2.52)	(-0.50)	(4.74)	(0.82)	(2.36)	(-0.57)	(3.41)
δ_c	-0.00597***	0.00459	-0.0181**	-0.00658***	-0.00598***	0.00455	-0.0180**	-0.00657***	-0.00554***	0.00779	-0.0201**	-0.00663***
	(-6.81)	(0.77)	(-2.38)	(-8.02)	(-6.83)	(0.77)	(-2.37)	(-8.02)	(-6.09)	(1.03)	(-2.02)	(-8.09)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00653	-0.0592	-0.0697	-0.00757	0.00820	-0.0576	-0.0695	-0.00573	0.00632	-0.0572	-0.0808	-0.00845
	(0.56)	(-1.41)	(-1.44)	(-0.68)	(0.70)	(-1.33)	(-1.42)	(-0.51)	(0.53)	(-1.15)	(-1.58)	(-0.74)
δ_c	-0.00531***	-0.00733*	-0.0106	-0.00648***	-0.00533***	-0.00733*	-0.0107	-0.00651***	-0.00529***	-0.00599	-0.00808	-0.00648***
	(-6.16)	(-1.82)	(-1.57)	(-7.74)	(-6.18)	(-1.82)	(-1.59)	(-7.76)	(-6.18)	(-1.34)	(-1.22)	(-7.77)

Table C.19.: *CATFAT* Liquidity Creation and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau-$ eff represents revenue efficiency, while $\pi-$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

						Panel A: $m = \tau - \text{eff}_{DEA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0217**	-0.0245	-0.0544	-0.0247***	-0.0226**	-0.0227	-0.0573	-0.0255***	-0.0202**	-0.0120	-0.0391	-0.0208**
	(-2.40)	(-0.61)	(-0.71)	(-2.76)	(-2.51)	(-0.56)	(-0.74)	(-2.86)	(-2.34)	(-0.31)	(-0.51)	(-2.43)
δ_c	-0.00522***	-0.00830**	-0.0135**	-0.00655***	-0.00522***	-0.00829**	-0.0134**	-0.00655***	-0.00518***	-0.00832**	-0.0151**	-0.00655***
	(-6.20)	(-2.10)	(-2.11)	(-8.01)	(-6.19)	(-2.10)	(-2.11)	(-8.01)	(-6.15)	(-2.07)	(-2.36)	(-8.00)
						Panel B: $m = \tau - \text{eff}_{SFA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0227***	-0.0698***	0.00340	-0.0132***	-0.0222***	-0.0694***	0.00355	-0.0128***	-0.0189***	-0.0730***	0.00282	-0.0136***
	(-4.89)	(-3.41)	(0.10)	(-3.47)	(-4.76)	(-3.40)	(0.11)	(-3.35)	(-4.28)	(-3.57)	(0.09)	(-3.54)
δ_c	-0.00475***	-0.0253***	-0.0142	-0.00662***	-0.00477***	-0.0252***	-0.0142	-0.00663***	-0.00497***	-0.0224***	-0.0147	-0.00665***
	(-5.58)	(-4.03)	(-0.84)	(-8.07)	(-5.60)	(-4.03)	(-0.84)	(-8.08)	(-5.87)	(-4.18)	(-1.05)	(-8.11)
						Panel C: $m = \tau - \text{eff}_{GFA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.317***	0.211**	-0.0307	0.131***	0.330***	0.211**	-0.0298	0.134***	0.0570	0.162**	-0.0345	0.0684***
	(4.92)	(2.48)	(-0.43)	(4.96)	(5.09)	(2.48)	(-0.42)	(5.03)	(1.37)	(2.35)	(-0.58)	(3.69)
δ_c	-0.00703***	0.00673	-0.0183**	-0.00659***	-0.00710***	0.00669	-0.0182**	-0.00659***	-0.00579***	0.00835	-0.0204**	-0.00664***
	(-7.48)	(1.00)	(-2.14)	(-8.04)	(-7.55)	(1.00)	(-2.14)	(-8.04)	(-6.25)	(1.08)	(-2.00)	(-8.11)
						Panel D: $m = \pi - \text{eff}_{DEA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.00758	-0.0633	-0.0785	-0.00381	0.00884	-0.0615	-0.0792	-0.00235	0.00736	-0.0639	-0.0842*	-0.00714
	(0.66)	(-1.48)	(-1.57)	(-0.35)	(0.77)	(-1.40)	(-1.56)	(-0.21)	(0.63)	(-1.31)	(-1.67)	(-0.63)
δ_c	-0.00531***	-0.00873**	-0.0126**	-0.00655***	-0.00532***	-0.00869**	-0.0127**	-0.00657***	-0.00528***	-0.00697*	-0.00949	-0.00653***
	(-6.19)	(-2.21)	(-1.98)	(-7.88)	(-6.19)	(-2.20)	(-2.00)	(-7.89)	(-6.20)	(-1.70)	(-1.50)	(-7.87)

Next I consider the $CATNONFAT$ liquidity measure, which excludes off-balance-sheet items in the calculation of liquidity creation in Tables C.20-C.21.

In general, the results are very similar to those found for $CATFAT$. Specifically, the SFA-based MA variable strongly suggests that banks that were more ably managed before the crisis contracted their liquidity creation more as a reaction to the crisis. Again, this result is supported by DEA for both revenue- and profit efficiency-based MA (Panel A and D). Additionally, the contrary evidence provided by GFA in Panel C is now much weaker than in the $CATFAT$ case. In fact, this method now confirms the main findings for large banks with significantly negative coefficients for all choices of first stage Tobit regressors ($r = 1, \ldots, 3$). These findings are not sensitive to the choice of pooled Tobit regressions versus the yearly approach, as is documented by Table C.21. Again, this analysis shows that the main conclusions are not merely driven by the choice of MA measure.

Table C.20.: $CATNONFAT$ Liquidity Creation and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0389***	-0.0113	-0.00489	-0.0368***	-0.0390***	-0.00960	-0.00366	-0.0369***	-0.0330***	0.00879	0.0491	-0.0296***
	(-4.48)	(-0.25)	(-0.08)	(-4.31)	(-4.50)	(-0.21)	(-0.06)	(-4.32)	(-4.26)	(0.22)	(0.82)	(-3.85)
δ_c	-0.00239***	-0.00107	-0.00217	-0.00255***	-0.00239***	-0.00109	-0.00227	-0.00255***	-0.00226***	-0.00106	-0.00370	-0.00254***
	(-3.21)	(-0.35)	(-0.35)	(-3.60)	(-3.21)	(-0.36)	(-0.37)	(-3.59)	(-3.04)	(-0.33)	(-0.70)	(-3.57)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0127***	-0.0355**	0.0304	-0.00846**	-0.0122***	-0.0356**	0.0305	-0.00813**	-0.00894**	-0.0398**	0.0275	-0.00722**
	(-2.96)	(-2.02)	(1.18)	(-2.55)	(-2.84)	(-2.01)	(1.20)	(-2.44)	(-2.21)	(-2.15)	(1.13)	(-2.11)
δ_c	-0.00197***	-0.0107*	0.0101	-0.00257***	-0.00199***	-0.0107*	0.0101	-0.00257***	-0.00214***	-0.00940*	0.00621	-0.00258***
	(-2.58)	(-1.90)	(0.76)	(-3.62)	(-2.61)	(-1.89)	(0.77)	(-3.62)	(-2.84)	(-1.96)	(0.59)	(-3.64)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.183***	0.107	-0.155***	0.0604**	0.187***	0.107	-0.154***	0.0616**	-0.00844	0.0732	-0.134***	-0.00128
	(4.20)	(1.37)	(-2.70)	(2.48)	(4.28)	(1.36)	(-2.69)	(2.52)	(-0.25)	(1.25)	(-3.11)	(-0.08)
δ_c	-0.00303***	0.00471	-0.0129*	-0.00255***	-0.00304***	0.00467	-0.0128*	-0.00255***	-0.00220***	0.00604	-0.0211***	-0.00256***
	(-3.88)	(0.95)	(-1.96)	(-3.59)	(-3.90)	(0.94)	(-1.95)	(-3.59)	(-2.78)	(0.96)	(-2.63)	(-3.60)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0129	-0.0349	-0.0116	-0.0157*	-0.0117	-0.0330	-0.00986	-0.0144	-0.0120	-0.0249	-0.0253	-0.0140
	(-1.28)	(-1.00)	(-0.29)	(-1.67)	(-1.15)	(-0.91)	(-0.24)	(-1.52)	(-1.16)	(-0.64)	(-0.63)	(-1.46)
δ_c	-0.00213***	-0.000770	-0.00173	-0.00234***	-0.00215***	-0.000781	-0.00187	-0.00236***	-0.00218***	-0.000294	-0.000223	-0.00238***
	(-2.80)	(-0.25)	(-0.29)	(-3.22)	(-2.82)	(-0.25)	(-0.32)	(-3.24)	(-2.88)	(-0.09)	(-0.04)	(-3.28)

Table C.21.: $CATNONFAT$ Liquidity Creation and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATNONFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0362***	-0.00761	0.0200	-0.0338***	-0.0369***	-0.00637	0.0202	-0.0344***	-0.0349***	0.00133	0.0423	-0.0316***
	(-4.54)	(-0.19)	(0.34)	(-4.29)	(-4.64)	(-0.16)	(0.34)	(-4.38)	(-4.57)	(0.03)	(0.72)	(-4.20)
δ_c	-0.00226***	-0.00127	-0.00330	-0.00251***	-0.00225***	-0.00126	-0.00329	-0.00251***	-0.00219***	-0.00115	-0.00298	-0.00250***
	(-3.03)	(-0.40)	(-0.60)	(-3.54)	(-3.02)	(-0.40)	(-0.60)	(-3.54)	(-2.94)	(-0.34)	(-0.56)	(-3.53)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0115***	-0.0372**	0.0308	-0.00816**	-0.0111***	-0.0371**	0.0311	-0.00787**	-0.00895**	-0.0415**	0.0261	-0.00741**
	(-2.75)	(-2.07)	(1.20)	(-2.45)	(-2.64)	(-2.06)	(1.21)	(-2.35)	(-2.24)	(-2.23)	(1.07)	(-2.18)
δ_c	-0.00204***	-0.0104*	0.00936	-0.00258***	-0.00205***	-0.0104*	0.00941	-0.00258***	-0.00216***	-0.00935**	0.00551	-0.00259***
	(-2.68)	(-1.92)	(0.75)	(-3.63)	(-2.70)	(-1.91)	(0.75)	(-3.63)	(-2.86)	(-1.98)	(0.53)	(-3.65)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.252***	0.0978	-0.143***	0.0424*	0.262***	0.0974	-0.142**	0.0439*	-0.00593	0.0729	-0.136***	-0.000272
	(4.43)	(1.32)	(-2.60)	(1.88)	(4.56)	(1.31)	(-2.59)	(1.95)	(-0.17)	(1.23)	(-3.13)	(-0.02)
δ_c	-0.00371***	0.00566	-0.0153**	-0.00256***	-0.00376***	0.00562	-0.0152**	-0.00256***	-0.00223***	0.00620	-0.0217***	-0.00256***
	(-4.44)	(0.99)	(-2.09)	(-3.60)	(-4.50)	(0.98)	(-2.08)	(-3.60)	(-2.77)	(0.96)	(-2.66)	(-3.60)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0158	-0.0356	-0.0139	-0.0179*	-0.0150	-0.0334	-0.0127	-0.0170*	-0.0137	-0.0310	-0.0260	-0.0163*
	(-1.60)	(-1.00)	(-0.35)	(-1.94)	(-1.52)	(-0.91)	(-0.31)	(-1.82)	(-1.35)	(-0.80)	(-0.67)	(-1.71)
δ_c	-0.00213***	-0.00158	-0.00203	-0.00237***	-0.00213***	-0.00154	-0.00209	-0.00238***	-0.00220***	-0.000668	-0.000689	-0.00241***
	(-2.81)	(-0.51)	(-0.37)	(-3.30)	(-2.81)	(-0.49)	(-0.39)	(-3.31)	(-2.92)	(-0.21)	(-0.13)	(-3.35)

Finally, I consider the findings that obtain if the liquidity transformation gap of Deep and Schaefer (2004) is used as indicator of liquidity creation. These findings are tabulated in C.22-C.23.

Again, with the exception of large banks, the SFA-based MA results indicate that more able pre-crisis management led banks to reduce their liquidity creation more after the onset of the crisis. Moreover, for $r = 2, 3$ a significantly negative relation obtains also for medium banks. These findings are confirmed by the DEA revenue efficiency-based results in Panel A for small banks and the full sample and by the negative coefficients that mostly prevail in Panel D. GFA in Panel C suggests a contrary interpretation for the first and second set of first stage Tobit regressors ($r = 1, 2$), however this evidence disappears for $r = 3$. This contrary evidence is also substantially weakened (fewer and less significant coefficients) as one transitions to pooled Tobit regressions in Table C.23. So, once more, the main conclusions do not appear to be driven by the choice of MA parametrization.

Table C.22.: *LTG* Liquidity Creation and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of Deep and Schaefer's (2004) liquidity transformation gap measure of liquidity creation (LTG) scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

						Panel A: $m = \tau - \text{eff}_{DEA}$						
			$r = 1$				$r = 2$				$r = 3$	
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0817***	0.0583	0.0449	-0.0752***	-0.0823***	0.0605	0.0482	-0.0757***	-0.0649***	0.0597	0.0972	-0.0577***
	(-7.22)	(1.16)	(0.67)	(-6.93)	(-7.26)	(1.18)	(0.71)	(-6.95)	(-6.32)	(1.36)	(1.60)	(-5.83)
δ_c	-0.00815***	-0.0160***	-0.0185**	-0.00860***	-0.00815***	-0.0160***	-0.0187**	-0.00860***	-0.00788***	-0.0146***	-0.0174**	-0.00858***
	(-8.32)	(-3.48)	(-2.22)	(-9.25)	(-8.32)	(-3.49)	(-2.25)	(-9.24)	(-8.04)	(-3.11)	(-2.50)	(-9.21)
						Panel B: $m = \tau - \text{eff}_{SFA}$						
			$r = 1$				$r = 2$				$r = 3$	
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0227***	-0.0346	0.0519*	-0.0122***	-0.0221***	-0.0348	0.0518*	-0.0118***	-0.0126**	-0.0354	0.0528*	-0.00772*
	(-4.10)	(-1.59)	(1.79)	(-2.75)	(-3.98)	(-1.60)	(1.78)	(-2.66)	(-2.45)	(-1.54)	(1.87)	(-1.74)
δ_c	-0.00736***	-0.0247***	0.00654	-0.00864***	-0.00739***	-0.0247***	0.00640	-0.00864***	-0.00773***	-0.0227***	0.00178	-0.00865***
	(-7.36)	(-3.29)	(0.45)	(-9.24)	(-7.39)	(-3.31)	(0.44)	(-9.25)	(-7.78)	(-3.53)	(0.15)	(-9.26)
						Panel C: $m = \tau - \text{eff}_{GFA}$						
			$r = 1$				$r = 2$				$r = 3$	
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.0676	0.139	-0.0947	0.0570*	0.0719	0.138	-0.0941	0.0583*	-0.110**	0.0755	-0.0755	0.00360
	(1.19)	(1.37)	(-1.29)	(1.83)	(1.26)	(1.37)	(-1.29)	(1.87)	(-2.36)	(0.96)	(-1.37)	(0.17)
δ_c	-0.00820***	-0.00780	-0.0214***	-0.00861***	-0.00822***	-0.00786	-0.0213***	-0.00861***	-0.00689***	-0.00798	-0.0255***	-0.00862***
	(-8.03)	(-1.13)	(-2.66)	(-9.21)	(-8.04)	(-1.14)	(-2.65)	(-9.21)	(-6.54)	(-0.89)	(-2.74)	(-9.22)
						Panel D: $m = \pi - \text{eff}_{DEA}$						
			$r = 1$				$r = 2$				$r = 3$	
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0204	-0.00553	-0.0188	-0.0217*	-0.0201	-0.00576	-0.0168	-0.0212*	-0.0289**	0.00282	-0.0203	-0.0299**
	(-1.52)	(-0.11)	(-0.40)	(-1.75)	(-1.49)	(-0.11)	(-0.35)	(-1.69)	(-2.10)	(0.05)	(-0.42)	(-2.35)
δ_c	-0.00769***	-0.0154***	-0.0137*	-0.00832***	-0.00769***	-0.0154***	-0.0139*	-0.00832***	-0.00768***	-0.0155***	-0.0132*	-0.00824***
	(-7.67)	(-3.29)	(-1.78)	(-8.70)	(-7.67)	(-3.28)	(-1.80)	(-8.70)	(-7.71)	(-3.09)	(-1.76)	(-8.66)

Table C.23.: LTG Liquidity Creation and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of Deep and Schaefer's (2004) liquidity transformation gap measure of liquidity creation (LTG) scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
Panel A: $m = \tau - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0685***	0.0499	0.0651	-0.0621***	-0.0693***	0.0514	0.0680	-0.0628***	-0.0596***	0.0545	0.102*	-0.0519***
	(-6.50)	(1.14)	(1.04)	(-6.12)	(-6.60)	(1.16)	(1.07)	(-6.20)	(-5.88)	(1.27)	(1.72)	(-5.32)
δ_c	-0.00787***	-0.0149***	-0.0175**	-0.00853***	-0.00786***	-0.0148***	-0.0175**	-0.00853***	-0.00777***	-0.0141***	-0.0161**	-0.00853***
	(-8.03)	(-3.20)	(-2.38)	(-9.17)	(-8.02)	(-3.18)	(-2.39)	(-9.16)	(-7.92)	(-2.94)	(-2.36)	(-9.15)
Panel B: $m = \tau - \text{eff}_{SFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0220***	-0.0366	0.0522*	-0.0130***	-0.0215***	-0.0367*	0.0521*	-0.0126***	-0.0150***	-0.0389*	0.0513*	-0.0101**
	(-4.10)	(-1.65)	(1.78)	(-2.93)	(-3.99)	(-1.65)	(1.78)	(-2.85)	(-2.96)	(-1.70)	(1.82)	(-2.29)
δ_c	-0.00745***	-0.0245***	0.00513	-0.00865***	-0.00747***	-0.0245***	0.00499	-0.00866***	-0.00772***	-0.0231***	0.000753	-0.00867***
	(-7.48)	(-3.38)	(0.37)	(-9.26)	(-7.50)	(-3.39)	(0.36)	(-9.26)	(-7.79)	(-3.66)	(0.06)	(-9.28)
Panel C: $m = \tau - \text{eff}_{GFA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.195**	0.121	-0.0679	0.0737**	0.206***	0.120	-0.0672	0.0754***	-0.0888*	0.0752	-0.0747	0.0114
	(2.57)	(1.27)	(-0.98)	(2.53)	(2.70)	(1.26)	(-0.97)	(2.58)	(-1.81)	(0.95)	(-1.34)	(0.55)
δ_c	-0.00903***	-0.00699	-0.0211**	-0.00862***	-0.00909***	-0.00708	-0.0211**	-0.00862***	-0.00706***	-0.00781	-0.0256***	-0.00863***
	(-8.33)	(-0.89)	(-2.38)	(-9.22)	(-8.37)	(-0.91)	(-2.38)	(-9.22)	(-6.58)	(-0.86)	(-2.71)	(-9.23)
Panel D: $m = \pi - \text{eff}_{DEA}$	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0170	-0.00377	-0.0198	-0.0167	-0.0167	-0.00329	-0.0179	-0.0162	-0.0187	-0.000232	-0.0126	-0.0199
	(-1.30)	(-0.07)	(-0.43)	(-1.36)	(-1.27)	(-0.06)	(-0.38)	(-1.31)	(-1.40)	(-0.00)	(-0.28)	(-1.59)
δ_c	-0.00776***	-0.0155***	-0.0143**	-0.00845***	-0.00776***	-0.0155***	-0.0144**	-0.00845***	-0.00781***	-0.0154***	-0.0142**	-0.00844***
	(-7.76)	(-3.32)	(-2.01)	(-8.91)	(-7.76)	(-3.32)	(-2.03)	(-8.91)	(-7.87)	(-3.27)	(-2.00)	(-8.93)

Overall, this section shows that there is robust support for the interpretation that more able pre-crisis management of banks induced these institutions to curtail their intermediation activity more strongly during the crisis itself, consistent with A3b. This interpretation of the data is particularly salient when SFA-based revenue efficiency is used for the parametrization of MA and proves robust to changes in the parametrization of efficiency scores that are used as a basis for the MA measure, to the sampling of the first stage Tobit regressions (yearly vs pooled) as well as to the choice of regressors employed in these first stage regressions.

C.1.4.2. Effects on Bank Risk-Taking

As before for the case of liquidity creation, I investigate the robustness of the findings regarding bank risk. Again the main concern is with the impact that the choice of MA parametrization has on the findings. The regressions are of the following form, with all variables as previously defined:

$$KRI_{k,i,t} = \alpha + \beta_1 \delta_c + \beta_2 MA^r_{m,s,i,06} \times \delta_c + \boldsymbol{\xi}' \mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}. \tag{C.6}$$

In terms of nonperforming loans, the main analysis finds, tentatively, that pre-crisis managerial ability further decreased the quantity of nonperforming loans during the crisis. Tables C.24-C.25, show that this result, replicated in Panel D, for $r = 1$ of Table C.24, is robust to the choice of first stage Tobit regressors ($r = 2, 3$). Moreover, the table also shows that this result is strongly supported by the results in Panels A and C. This holds for yearly regressions (see Table C.24) as well as, albeit in somewhat weaker form for pooled regressions (see Table C.25). The only contrary evidence is provided by the results using SFA-based revenue efficiency as the basis for managerial ability (Panel B).

Table C.24.: Nonperforming Loans (NPL) and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of the ratio of nonperforming loans over total loans (NPL) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

					Panel A: $m = \tau - \text{eff}_{DEA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0212***	-0.00627	-0.00769	-0.0176***	-0.0212***	-0.00552	-0.00782	-0.0176***	-0.0145***	0.000634	-0.00286	-0.0133***
	(-8.58)	(-0.44)	(-0.60)	(-7.29)	(-8.58)	(-0.39)	(-0.60)	(-7.29)	(-6.47)	(0.05)	(-0.24)	(-6.04)
δ_c	0.00561***	0.00822***	0.0103***	0.00640***	0.00561***	0.00821***	0.0103***	0.00640***	0.00568***	0.00817***	0.00974***	0.00641***
	(23.79)	(6.49)	(6.13)	(28.03)	(23.79)	(6.49)	(6.19)	(28.03)	(23.95)	(6.53)	(7.14)	(28.09)
					Panel B: $m = \tau - \text{eff}_{SFA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.00972***	0.00408	0.00410	0.00382***	0.00961***	0.00358	0.00411	0.00370***	0.00765***	0.00378	0.00611	0.00425***
	(7.95)	(0.69)	(0.55)	(3.80)	(7.82)	(0.61)	(0.56)	(3.67)	(6.81)	(0.66)	(0.79)	(4.28)
δ_c	0.00543***	0.00925***	0.0114***	0.00640***	0.00544***	0.00911***	0.0114***	0.00640***	0.00555***	0.00894***	0.0116***	0.00641***
	(23.06)	(4.53)	(3.07)	(28.01)	(23.07)	(4.53)	(3.13)	(28.01)	(23.54)	(5.12)	(3.76)	(28.08)
					Panel C: $m = \tau - \text{eff}_{GFA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.0514***	-0.0560**	-0.0281	-0.0114	0.0506***	-0.0562**	-0.0281	-0.0118	0.0142	-0.0377**	-0.0343***	-0.0220***
	(4.04)	(-2.28)	(-1.49)	(-1.52)	(3.96)	(-2.29)	(-1.49)	(-1.57)	(1.40)	(-1.97)	(-2.85)	(-4.41)
δ_c	0.00546***	0.00508***	0.00779***	0.00640***	0.00546***	0.00508***	0.00779***	0.00640***	0.00554***	0.00444**	0.00493**	0.00641***
	(22.35)	(3.12)	(3.97)	(28.03)	(22.35)	(3.13)	(3.97)	(28.03)	(22.28)	(2.21)	(2.38)	(28.28)
					Panel D: $m = \pi - \text{eff}_{DEA}$							
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.0198***	-0.00599	0.00918	-0.0143***	-0.0202***	-0.00400	0.00956	-0.0146***	-0.00917***	0.00558	0.00178	-0.00395
	(-6.64)	(-0.62)	(0.95)	(-5.15)	(-6.72)	(-0.41)	(0.97)	(-5.20)	(-3.01)	(0.52)	(0.16)	(-1.39)
δ_c	0.00590***	0.00823***	0.00902***	0.00660***	0.00591***	0.00821***	0.00901***	0.00660***	0.00575***	0.00796***	0.00950***	0.00645***
	(24.34)	(6.57)	(6.32)	(28.30)	(24.36)	(6.55)	(6.37)	(28.31)	(24.00)	(6.00)	(6.05)	(27.96)

Table C.25.: Nonperforming Loans (NPL) and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of the ratio of nonperforming loans over total loans (NPL) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0205***	-0.00581	-0.00259	-0.0187***	-0.0202***	-0.00507	-0.00235	-0.0184***	-0.0181***	-0.000570	0.00294	-0.0169***
	(-8.78)	(-0.43)	(-0.22)	(-8.22)	(-8.68)	(-0.38)	(-0.19)	(-8.11)	(-8.06)	(-0.04)	(0.24)	(-7.71)
δ_c	0.00568***	0.00809***	0.00977***	0.00642***	0.00569***	0.00810***	0.00975***	0.00642***	0.00572***	0.00815***	0.00964***	0.00643***
	(24.05)	(6.48)	(6.89)	(28.18)	(24.05)	(6.47)	(6.94)	(28.18)	(24.13)	(6.37)	(7.22)	(28.22)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.0104***	0.00474	0.00436	0.00494***	0.0102***	0.00422	0.00432	0.00479***	0.00865***	0.00497	0.00599	0.00522***
	(8.71)	(0.79)	(0.58)	(4.91)	(8.55)	(0.71)	(0.58)	(4.74)	(7.79)	(0.85)	(0.79)	(5.28)
δ_c	0.00544***	0.00934***	0.0114***	0.00641***	0.00545***	0.00920***	0.0113***	0.00641***	0.00555***	0.00914***	0.0115***	0.00642***
	(23.22)	(4.68)	(3.23)	(28.04)	(23.23)	(4.69)	(3.28)	(28.05)	(23.61)	(5.24)	(3.83)	(28.12)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.0216	-0.0461**	-0.0248	-0.0273***	0.0187	-0.0459**	-0.0248	-0.0277***	-0.0111	-0.0381**	-0.0337***	-0.0277***
	(1.30)	(-2.05)	(-1.36)	(-4.05)	(1.12)	(-2.04)	(-1.37)	(-4.12)	(-1.05)	(-1.98)	(-2.74)	(-5.63)
δ_c	0.00555***	0.00494***	0.00745***	0.00640***	0.00556***	0.00496***	0.00745***	0.00640***	0.00578***	0.00430**	0.00493**	0.00642***
	(21.48)	(2.74)	(3.27)	(28.12)	(21.49)	(2.76)	(3.29)	(28.13)	(22.80)	(2.08)	(2.30)	(28.38)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.0235***	-0.00544	0.00782	-0.0195***	-0.0238***	-0.00329	0.00826	-0.0197***	-0.0145***	0.00613	0.00738	-0.00913***
	(-7.97)	(-0.55)	(0.82)	(-7.09)	(-8.03)	(-0.33)	(0.83)	(-7.11)	(-4.83)	(0.58)	(0.65)	(-3.22)
δ_c	0.00591***	0.00810***	0.00937***	0.00660***	0.00591***	0.00812***	0.00937***	0.00660***	0.00576***	0.00806***	0.00914***	0.00648***
	(24.49)	(6.46)	(6.96)	(28.55)	(24.51)	(6.47)	(7.01)	(28.57)	(24.10)	(6.37)	(6.41)	(28.21)

Concerning results on tier 1 capital, the main analysis finds that more able management pre crisis ensured a smaller decline or even an increase in $T1R$ during the crisis. These main results are replicated in Panel D, $r = 1$ of Table C.26. I find that this result is not driven by the selection of first stage regressors ($r = 1, \ldots, 3$). Additionally, SFA revenue efficiency confirms this finding for small banks and DEA revenue efficiency also confirms this result for small banks and the full sample when $r = 3$. Only GFA provides divergent evidence, especially for large banks and the full sample of banks. Overall, these findings strengthen as one passes to a pooled Tobit regression in Table C.27. This not only suggests that more able managers reacted more effectively to the crisis but also that, as conjectured in the main analysis, large banks may have been more difficult to de-risk. This may possibly have been the case due to their greater interconnectedness with the global financial markets. Thus the majority of the evidence again supports the main interpretation.

Table C.26.: Tier 1 Ratio ($T1R$) and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of the ratio of tier 1 capital over total assets ($T1R$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00536	0.0249	-0.00826	0.00574	0.00476	0.0245	-0.00927	0.00515	0.0202***	0.0213	-0.00119	0.0186***
	(1.52)	(1.00)	(-0.74)	(1.58)	(1.34)	(0.98)	(-0.82)	(1.41)	(6.33)	(0.95)	(-0.12)	(5.62)
δ_c	-0.000390	-0.000538	-0.00207	-0.000397	-0.000392	-0.000528	-0.00200	-0.000397	-0.000418	0.000000904	-0.00267	-0.000409
	(-1.21)	(-0.49)	(-1.04)	(-1.34)	(-1.22)	(-0.48)	(-1.00)	(-1.34)	(-1.30)	(0.00)	(-1.51)	(-1.38)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00833***	0.000769	-0.0104*	0.00209	0.00865***	0.000928	-0.00981	0.00231	0.0119***	0.00170	-0.00843*	0.00639***
	(4.22)	(0.09)	(-1.74)	(1.47)	(4.40)	(0.10)	(-1.65)	(1.62)	(6.39)	(0.20)	(-1.66)	(4.27)
δ_c	-0.000611*	-0.0000913	-0.00702**	-0.000393	-0.000615*	-0.0000500	-0.00676**	-0.000391	-0.000592*	0.0000527	-0.00539**	-0.000372
	(-1.84)	(-0.03)	(-2.11)	(-1.33)	(-1.85)	(-0.02)	(-2.03)	(-1.33)	(-1.81)	(0.02)	(-2.04)	(-1.26)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.00320	-0.0245	-0.0328*	-0.0393***	-0.00275	-0.0244	-0.0327*	-0.0391***	-0.0439***	-0.0123	-0.0162	-0.0316***
	(-0.16)	(-0.75)	(-1.85)	(-3.49)	(-0.14)	(-0.74)	(-1.84)	(-3.47)	(-3.19)	(-0.45)	(-1.36)	(-4.43)
δ_c	-0.000391	-0.00164	-0.00489**	-0.000400	-0.000393	-0.00163	-0.00488**	-0.000400	0.0000101	-0.00151	-0.00494**	-0.000374
	(-1.17)	(-0.84)	(-2.24)	(-1.35)	(-1.18)	(-0.84)	(-2.24)	(-1.35)	(0.03)	(-0.55)	(-2.11)	(-1.27)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00305	0.0207**	-0.00338	0.00314	0.00143	0.0188**	-0.00415	0.00152	0.00616	0.0154	-0.00180	0.00630*
	(0.80)	(2.24)	(-0.33)	(0.91)	(0.37)	(2.09)	(-0.39)	(0.45)	(1.57)	(1.42)	(-0.12)	(1.78)
δ_c	-0.000440	-0.000540	-0.00246	-0.000439	-0.000421	-0.000525	-0.00241	-0.000417	-0.000458	-0.000846	-0.00253	-0.000475
	(-1.34)	(-0.46)	(-1.08)	(-1.43)	(-1.28)	(-0.45)	(-1.06)	(-1.36)	(-1.41)	(-0.74)	(-0.92)	(-1.56)

Table C.27.: Tier 1 Ratio ($T1R$) and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of the ratio of tier 1 capital over total assets ($T1R$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.0137***	0.0221	-0.00530	0.0126***	0.0135***	0.0216	-0.00610	0.0124***	0.0201***	0.0204	-0.00189	0.0181***
	(4.19)	(1.00)	(-0.50)	(3.72)	(4.12)	(0.99)	(-0.58)	(3.66)	(6.40)	(0.95)	(-0.19)	(5.62)
δ_c	-0.000415	-0.0000456	-0.00250	-0.000413	-0.000417	-0.0000425	-0.00248	-0.000414	-0.000457	0.000209	-0.00268	-0.000427
	(-1.29)	(-0.03)	(-1.36)	(-1.39)	(-1.30)	(-0.03)	(-1.35)	(-1.40)	(-1.42)	(0.14)	(-1.54)	(-1.44)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00963***	0.000867	-0.0102*	0.00347**	0.00982***	0.000995	-0.00968	0.00359**	0.0128***	0.00113	-0.00848*	0.00724***
	(4.96)	(0.10)	(-1.74)	(2.38)	(5.06)	(0.11)	(-1.65)	(2.47)	(6.89)	(0.13)	(-1.68)	(4.80)
δ_c	-0.000613*	-0.0000821	-0.00663**	-0.000387	-0.000613*	-0.0000510	-0.00642**	-0.000385	-0.000583*	-0.0000748	-0.00531**	-0.000362
	(-1.86)	(-0.03)	(-2.11)	(-1.31)	(-1.86)	(-0.02)	(-2.04)	(-1.31)	(-1.79)	(-0.03)	(-2.04)	(-1.23)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.00414	-0.0228	-0.0289*	-0.0381***	-0.00618	-0.0228	-0.0287*	-0.0385***	-0.0618***	-0.0133	-0.0165	-0.0344***
	(-0.16)	(-0.72)	(-1.83)	(-3.64)	(-0.24)	(-0.72)	(-1.83)	(-3.66)	(-4.27)	(-0.48)	(-1.37)	(-4.81)
δ_c	-0.000381	-0.00189	-0.00529**	-0.000395	-0.000370	-0.00189	-0.00526**	-0.000396	0.000200	-0.00164	-0.00502**	-0.000368
	(-1.07)	(-0.82)	(-2.26)	(-1.34)	(-1.03)	(-0.82)	(-2.26)	(-1.34)	(0.59)	(-0.58)	(-2.12)	(-1.25)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.00446	0.0198**	-0.00360	-0.00427	-0.00563	0.0181*	-0.00437	-0.00551	0.00370	0.0139	-0.00279	0.00366
	(-1.20)	(2.03)	(-0.36)	(-1.26)	(-1.51)	(1.88)	(-0.42)	(-1.62)	(0.97)	(1.31)	(-0.20)	(1.06)
δ_c	-0.000360	-0.0000763	-0.00256	-0.000352	-0.000348	-0.000102	-0.00254	-0.000339	-0.000427	-0.000528	-0.00250	-0.000428
	(-1.10)	(-0.06)	(-1.29)	(-1.17)	(-1.07)	(-0.09)	(-1.27)	(-1.13)	(-1.32)	(-0.46)	(-1.04)	(-1.42)

The final analysis in this section checks, in Tables C.28-C.29, whether the results related to liquid assets over total assets are robust. Overall the main findings hold. Specifically, the choice of first stage Tobit regressors does not drive the results obtained from DEA profit efficiency (Panel D, $r = 1, \ldots, 3$). Specifically, for small banks and the full sample, liquid assets increase more for more ably managed banks. Similar results are yielded by SFA-revenue efficiency in Panel B. However in this case, the opposite result obtains for large banks, which supports the interpretation that these may have been too complex to handle during the crisis. Again, only GFA provides contrary evidence, while DEA revenue efficiency-based MA is uninformative. These results are not driven by the choice of yearly over pooled Tobit regressions to obtain MA as can be seen from Table C.29. So, in sum, more ably managed banks are found to de-risk more effectively.

Table C.28.: Liquid Assets ($LAGTA$) and Managerial Ability During the Financial Crisis, $s = y$.

This table reports results from fixed effects regressions of the ratio of liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau -$ eff represents revenue efficiency, while $\pi -$ eff represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

						Panel A: $m = \tau - \text{eff}_{DEA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.0129	-0.00724	-0.0175	0.0127	0.0128	-0.00883	-0.0175	0.0127	-0.00223	-0.0190	-0.0723	-0.00374
	(1.44)	(-0.22)	(-0.31)	(1.48)	(1.43)	(-0.27)	(-0.31)	(1.47)	(-0.27)	(-0.68)	(-1.40)	(-0.48)
δ_c	0.00538***	0.00408	0.00360	0.00579***	0.00538***	0.00409	0.00358	0.00579***	0.00535***	0.00374	0.00395	0.00579***
	(6.77)	(1.45)	(0.65)	(7.70)	(6.77)	(1.45)	(0.64)	(7.70)	(6.72)	(1.29)	(0.81)	(7.71)
						Panel B: $m = \tau - \text{eff}_{SFA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.0191***	0.0161	-0.0409*	0.0116***	0.0182***	0.0169	-0.0410*	0.0110***	0.0142***	0.0240	-0.0411*	0.0102***
	(4.10)	(0.98)	(-1.90)	(3.31)	(3.90)	(1.03)	(-1.90)	(3.13)	(3.22)	(1.41)	(-1.96)	(2.83)
δ_c	0.00487***	0.00832	-0.0148	0.00581***	0.00490***	0.00850	-0.0147	0.00581***	0.00512***	0.00896*	-0.0108	0.00583***
	(5.99)	(1.52)	(-1.34)	(7.72)	(6.04)	(1.56)	(-1.34)	(7.73)	(6.36)	(1.90)	(-1.19)	(7.75)
						Panel C: $m = \tau - \text{eff}_{GFA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	-0.251***	-0.0963	0.0713	-0.0910***	-0.259***	-0.0953	0.0705	-0.0932***	-0.173***	-0.0910*	0.0730*	-0.0441***
	(-5.15)	(-1.41)	(1.27)	(-3.66)	(-5.30)	(-1.40)	(1.26)	(-3.75)	(-5.17)	(-1.76)	(1.68)	(-2.79)
δ_c	0.00637***	-0.00128	0.00701	0.00578***	0.00640***	-0.00122	0.00696	0.00578***	0.00698***	-0.00497	0.0123*	0.00582***
	(7.68)	(-0.27)	(1.13)	(7.69)	(7.71)	(-0.25)	(1.13)	(7.69)	(8.49)	(-0.83)	(1.69)	(7.75)
						Panel D: $m = \pi - \text{eff}_{DEA}$						
	$r = 1$				$r = 2$				$r = 3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA^r_{m,s,06} \times \delta_c$	0.0334***	0.0314	0.0106	0.0326***	0.0307***	0.0319	0.0111	0.0305***	0.0139	0.00784	0.00739	0.0134
	(3.15)	(1.33)	(0.30)	(3.37)	(2.90)	(1.32)	(0.31)	(3.14)	(1.27)	(0.29)	(0.19)	(1.35)
δ_c	0.00495***	0.00364	0.00150	0.00534***	0.00498***	0.00362	0.00149	0.00537***	0.00522***	0.00373	0.00158	0.00562***
	(6.12)	(1.29)	(0.27)	(6.96)	(6.15)	(1.28)	(0.27)	(6.99)	(6.50)	(1.30)	(0.27)	(7.35)

Table C.29.: Liquid Assets ($LAGTA$) and Managerial Ability During the Financial Crisis, $s = p$.

This table reports results from fixed effects regressions of the ratio of liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and are suppressed. They include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. $MA^r_{m,s}$ represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012) using method m for efficiency as well as sample s (pooled, p or yearly y) and regressor set r for the Tobit regressions. Specification $r = 1$ uses regressors following Cantrell (2013) and Demerjian, Lev and McVay (2012), Specification $r = 2$ adds the holding company status variables, Specification $r = 3$ avoids potentially endogenous variables alltogether and substitutes bank demographic variables. m indicates the efficiency score used as a basis for managerial ability. Here $\tau - \text{eff}$ represents revenue efficiency, while $\pi - \text{eff}$ represents profit efficiency. DEA stands for data envelopment analysis, SFA stands for stochastic frontier analysis and GFA stands for generalized frontier analysis. Monetary values are in 2005 US Dollars.

	$r=1$				$r=2$				$r=3$			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
Panel A: $m = \tau - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.00799	-0.00177	-0.0440	0.00744	0.00899	-0.00378	-0.0447	0.00830	0.00590	-0.00890	-0.0725	0.00436
	(0.95)	(-0.06)	(-0.87)	(0.92)	(1.07)	(-0.13)	(-0.87)	(1.02)	(0.73)	(-0.32)	(-1.44)	(0.56)
δ_c	0.00534***	0.00399	0.00391	0.00578***	0.00534***	0.00396	0.00389	0.00578***	0.00533***	0.00379	0.00300	0.00578***
	(6.71)	(1.38)	(0.78)	(7.69)	(6.71)	(1.37)	(0.78)	(7.69)	(6.70)	(1.27)	(0.61)	(7.69)
Panel B: $m = \tau - \text{eff}_{SFA}$												
$MA^r_{m,s,06} \times \delta_c$	0.0152***	0.0159	-0.0421*	0.00950***	0.0146***	0.0167	-0.0423*	0.00907**	0.0102**	0.0217	-0.0407*	0.00701*
	(3.34)	(0.95)	(-1.94)	(2.68)	(3.20)	(1.00)	(-1.94)	(2.55)	(2.33)	(1.27)	(-1.94)	(1.94)
δ_c	0.00501***	0.00796	-0.0140	0.00582***	0.00503***	0.00814	-0.0140	0.00582***	0.00520***	0.00828*	-0.0103	0.00582***
	(6.20)	(1.50)	(-1.34)	(7.74)	(6.22)	(1.54)	(-1.33)	(7.74)	(6.48)	(1.79)	(-1.15)	(7.75)
Panel C: $m = \tau - \text{eff}_{GFA}$												
$MA^r_{m,s,06} \times \delta_c$	-0.365***	-0.0922	0.0558	-0.0692***	-0.382***	-0.0910	0.0552	-0.0718***	-0.175***	-0.0862*	0.0746*	-0.0400**
	(-5.84)	(-1.45)	(1.04)	(-3.09)	(-6.08)	(-1.44)	(1.03)	(-3.20)	(-4.97)	(-1.67)	(1.70)	(-2.54)
δ_c	0.00741***	-0.00244	0.00725	0.00579***	0.00750***	-0.00234	0.00719	0.00579***	0.00706***	-0.00472	0.0128*	0.00582***
	(8.45)	(-0.45)	(1.04)	(7.70)	(8.55)	(-0.44)	(1.03)	(7.70)	(8.50)	(-0.77)	(1.72)	(7.75)
Panel D: $m = \pi - \text{eff}_{DEA}$												
$MA^r_{m,s,06} \times \delta_c$	0.0448***	0.0334	0.0129	0.0430***	0.0430***	0.0337	0.0134	0.0416***	0.0295***	0.0194	0.00383	0.0284***
	(4.30)	(1.39)	(0.36)	(4.49)	(4.11)	(1.36)	(0.36)	(4.32)	(2.74)	(0.73)	(0.10)	(2.88)
δ_c	0.00489***	0.00438	0.00177	0.00535***	0.00491***	0.00437	0.00178	0.00537***	0.00516***	0.00369	0.00198	0.00554***
	(6.09)	(1.51)	(0.34)	(7.06)	(6.11)	(1.51)	(0.34)	(7.07)	(6.46)	(1.31)	(0.37)	(7.30)

Thus, overall, this section shows that the conclusions drawn from the analysis in Chapter 5 about the influence of managerial ability on bank risk during the crisis are robust to the parametrization of managerial ability and, hence, A4 ought to be accepted.

C.2. Further Robustness Checks

This section provides some further analyses on the robustness of the results. In cases where the findings unambiguously support the main conclusions I merely tabulate the results without providing any separate discussion. This is the case for all tests except for the placebo crisis. Here the results are also in line with the main findings but require some additional discussion.

More specifically, Section C.2.1 investigates how results change if one defines a placebo crisis and reruns the regressions. Concretely, I define a crisis for the years 2003-2004 with 2002 being the pre-crisis period. Section C.2.2 investigates how results change if potentially endogenous regressors are omitted from the analysis of liquidity creation and bank risk-taking. Specifically, the regressions omit $BKSIZE$, $CREDRSK$, $SDROA$ and $ZIND$ from the analysis. The analysis of liquidity creation conducted by Berger and Bouwman (2009) includes the equity over asset ratio as a regressor. In their case this is the main variable of interest. However, this variable may, as they explain at length, be endogenous to liquidity creation. Hence I have omitted it from the main analysis. However, it is important to ensure that this choice is not driving results. Hence Section C.2.3 reruns the regressions while including EA among the regressors. The main analysis includes the years 1996-2010. There may be concerns that the inclusion of the financial crisis period is somehow influencing the findings for normal times. Hence I rerun the analysis with a reduced sample that stops in 2006. These findings are reported in Section C.2.4. Further, it may be the case that the definition of the crisis period is driving results. Hence I reestimate the difference-in-differences models for a modified crisis definition 2008-2009 in Section C.2.5.1 and 2007-2008 in Section C.2.5.2. Specifically, I either designate 2006 as the last pre-crisis year and drop 2007 from the analysis or I drop data from 2009 onwards, inclusive. These analyses show that the initially insignificant coefficients on the interaction between MA and the crisis dummy in the main analysis are primarily due to the late period of the crisis (2008-2009). Here it appears that more ably managed banks in fact increase their liquidity creation. However the opposite is true initially, 2007-2008. This conforms with one's intuition. Specifically, if the theory of Bebchuk and Goldstein (2011) is true, then it is the general uncertainty about the evolution of the economy that drives banks to decrease their liquidity creation and one would naturally expect more able managers to do so more effectively. Once the crisis is well under way and being actively addressed by regulators as was the case in 2008-2009, much of that initial uncertainty disappears and hence the effect should reverse. This is in fact what the results indicate with some significantly positive coefficients on the interaction between MA and the crisis dummy for the period 2008-2009. In addition, one might raise the concern that managerial ability as observed in 2006 is not predetermined with respect to the financial crisis. To address this concern, Section C.2.6 reruns the difference-in-differences analysis using the interaction between the crisis dummy and managerial ability as of the year 2005. The final robustness check relates to the original analysis of Berger and Bouwman (2009). They combat endogeneity by using lagged 3-year moving averages of their regressors. I have opted to run the main analysis merely using the 3-year moving averages. To ensure that the choice to not lag regressors is not driving results, Section C.2.7 reruns the analysis with lagged 3-year moving averages of the regressors.

Overall, the original findings strengthen in some cases and weaken in others; but they are in general qualitatively robust. Most importantly, the relatively weak findings regarding the impact of managerial ability during the financial crisis strengthen remarkably throughout the majority of the robustness checks.

C.2.1. Placebo Crisis

This section reports results that are obtained for a placebo crisis in the years 2003-2004. Specifically, it designates 2002 as the last pre-crisis year and measures the impact of 2002 managerial ability on "crisis" liquidity creation and risk in Tables C.30 and C.31. Results are qualitatively similar if one defines the crisis for 2004-2005 and uses 2003-MA for example (unreported).

As regards the results for liquidity creation I find that a negative impact of "pre-crisis" managerial ability on "crisis" performance is not present, except for large banks. Moreover, the "crisis" dummy is positive. As expected this is the opposite of the main analysis because no crisis actually took place. No mergers took place in the sample, hence MRG is dropped. As regards the risk characteristics, Panel A shows a significantly negative coefficient on NPL (Panel A) for large banks, while the other coefficients are insignificant. All subsamples return insignificant coefficients for the tier 1 ratio (Panel B). Finally, the results for $LAGTA$ are similar to the main findings. Overall, the evidence shows that, while some mechanical patterns may exist in the data, their magnitude is not sufficient to drive the findings of the main analysis.

The subsequent sections unambiguously support the main findings and, therefore, include only tables without a separate discussion.

Table C.30.:
Impact of Managerial Ability on Bank Liquidity Creation During a Placebo Crisis, Defined as 2003-2004.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2002 interacted with a dummy for whether the observation is in the financial crisis ($MA_{02} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multi-bank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{02} \times \delta_c$	0.00752	-0.00643	-0.158***	-0.00120
	(0.52)	(-0.12)	(-3.25)	(-0.09)
δ_c	0.0254***	0.0137***	0.0255***	0.0249***
	(33.96)	(3.96)	(6.56)	(34.60)
$CREDRSK$	0.783***	0.934***	0.830***	0.792***
	(32.05)	(17.17)	(9.21)	(33.79)
$ZIND$	0.000273	-0.0000992	0.000756	0.000273
	(0.98)	(-0.09)	(0.60)	(1.04)
$SDROA$	-0.000411	-0.00110	-0.00116	-0.000648
	(-0.17)	(-0.08)	(-0.07)	(-0.28)
$BKSIZE$	0.00225	-0.0194	0.0219	0.00278
	(0.50)	(-1.14)	(0.97)	(0.68)
$BKHHI$	-0.00457	-0.139***	0.0512	-0.00644
	(-0.68)	(-2.78)	(0.80)	(-0.95)
$BKMSML$	0.0201***	0.0596	0.0305	0.0176***
	(3.96)	(1.54)	(0.50)	(3.56)
$BKPOP$	0.00762***	0.0167	-0.00971	0.00682***
	(2.91)	(1.02)	(-0.48)	(2.67)
$BKPDNS$	0.0198***	0.0321	-0.0312	0.0175**
	(2.65)	(1.10)	(-0.85)	(2.43)
$BKICHG$	0.0254***	0.268***	0.0499	0.0296***
	(2.67)	(3.91)	(0.36)	(3.14)
$MBHC$	0.0128**	-0.0105	0.0241	0.0127**
	(2.14)	(-0.62)	(1.57)	(2.21)
$OBHC$	0.00717	0.00148	0.00112	0.00696
	(1.49)	(0.12)	(0.10)	(1.47)
MRG	0	0	0	0
	(.)	(.)	(.)	(.)
ACQ	-0.000785	0.0108	-0.0211	0.000155
	(-0.31)	(1.17)	(-1.40)	(0.06)
Constant	-0.455***	-0.386	-0.354	-0.447***
	(-7.14)	(-1.54)	(-0.84)	(-7.44)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.567	0.700	0.628	0.571
N	17414	700	392	18506

Table C.31.: Impact of Managerial Ability on Bank Risk-Taking During a Placebo Crisis, Defined as 2003-2004.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2002 interacted with a dummy for whether the observation is in the financial crisis ($MA_{02} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{02} \times \delta_c$	-0.00256	-0.00527	-0.0173***	-0.00342	0.00165	0.0151	0.00319	0.00416	0.0537***	-0.0146	0.120**	0.0511***
	(-0.93)	(-0.99)	(-3.70)	(-1.40)	(0.29)	(0.64)	(0.19)	(0.64)	(3.01)	(-0.23)	(2.35)	(3.10)
δ_c	-0.00250***	-0.00219***	-0.00404***	-0.00250***	0.00257***	-0.000353	0.000718	0.00261***	-0.00142*	-0.00783	-0.0122**	-0.00139*
	(-16.51)	(-3.29)	(-6.25)	(-17.25)	(7.48)	(-0.19)	(0.33)	(7.50)	(-1.67)	(-1.32)	(-2.02)	(-1.67)
$CREDRSK$	0.0214***	0.0207**	0.0246**	0.0212***	-0.135***	-0.136***	-0.126***	-0.134***	-0.572***	-0.706***	-0.400***	-0.575***
	(7.70)	(2.09)	(2.58)	(7.92)	(-16.59)	(-4.29)	(-4.10)	(-16.92)	(-20.76)	(-6.84)	(-2.92)	(-21.45)
$ZIND$	-0.000176*	-0.000245	0.0000685	-0.000184**	0.000625**	0.00131	-0.000447	0.000658***	0.000367	-0.0000697	-0.000248	0.000332
	(-1.89)	(-0.95)	(0.22)	(-2.12)	(2.42)	(1.02)	(-0.69)	(2.60)	(0.61)	(-0.03)	(-0.07)	(0.57)
$SDROA$	0.00102	-0.00917***	0.00652	0.000962	0.000608	0.0578**	0.0201*	0.00251	0.00624	0.0625***	0.00281	0.00777
	(0.94)	(-3.32)	(1.37)	(0.93)	(0.24)	(2.19)	(1.85)	(0.87)	(0.95)	(2.59)	(0.09)	(1.22)
$BKSIZE$	0.00206**	0.000719	-0.00148	0.00178**	-0.00973***	-0.000410	-0.00922	-0.0110***	-0.00386	-0.00192	0.0241	-0.00438
	(2.37)	(0.34)	(-0.75)	(2.37)	(-4.15)	(-0.07)	(-1.33)	(-4.02)	(-0.60)	(-0.08)	(0.85)	(-0.75)
$BKHHI$	0.00109	0.0213	-0.00679	0.00123	-0.0108	0.340**	0.0705	-0.00291	-0.0317	0.207*	-0.304***	-0.0335*
	(0.32)	(1.52)	(-0.48)	(0.37)	(-1.32)	(2.16)	(1.52)	(-0.29)	(-1.58)	(1.72)	(-2.63)	(-1.69)
$BKMSML$	-0.00400**	-0.00277	0.00644	-0.00400**	0.00406	0.0390	0.0568**	0.00786	-0.00436	-0.00614	0.00570	-0.00403
	(-2.02)	(-0.52)	(1.03)	(-2.16)	(0.89)	(1.41)	(2.33)	(1.51)	(-0.34)	(-0.14)	(0.06)	(-0.33)
$BKPOP$	-0.00162**	-0.00735**	0.000203	-0.00161**	0.000789	-0.00592	0.00658*	0.00108	-0.00592	0.00122	0.00429	-0.00515
	(-2.37)	(-2.25)	(0.14)	(-2.48)	(0.44)	(-0.68)	(1.73)	(0.62)	(-1.14)	(0.07)	(0.22)	(-1.04)
$BKPDNS$	-0.00714***	0.00163	-0.00833*	-0.00659***	0.00357	0.00180	-0.0251	0.00408	-0.00738	-0.0779**	0.0435	-0.00521
	(-3.57)	(0.33)	(-1.78)	(-3.55)	(1.15)	(0.09)	(-1.54)	(1.35)	(-0.75)	(-2.56)	(0.98)	(-0.55)
$BKICHG$	-0.0191***	-0.0454	-0.140***	-0.0195***	0.00769	0.0559	0.0379	0.00924	0.0329	-0.522**	-0.216	0.0191
	(-3.30)	(-1.59)	(-4.30)	(-3.46)	(0.64)	(0.74)	(0.33)	(0.78)	(1.07)	(-2.29)	(-0.67)	(0.63)
$MBHC$	0.000354	-0.0122***	0.000214	0.0000460	0.000622	-0.0123	0.0031	-0.0000706	-0.000785	0.0949***	0.00021	0.000925
	(0.27)	(-5.14)	(0.20)	(0.04)	(0.18)	(-1.36)	(0.13)	(-0.02)	(-0.09)	(4.33)	(0.11)	(0.11)
$OBHC$	-0.00132	-0.00938***	-0.000705	-0.00135	0.00124	-0.00315	-0.00893	0.000800	-0.00470	0.0801***	-0.00598	-0.00392
	(-1.29)	(-4.97)	(-0.99)	(-1.37)	(0.45)	(-0.62)	(-1.31)	(0.29)	(-0.69)	(5.30)	(-0.44)	(-0.59)
MRG	0	0	0	0	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ACQ	0.000213	0.00254	0.000275	0.000323	0.0000784	0.000627	0.00603	0.000128	0.00375	-0.00461	-0.00486	0.00256
	(0.43)	(1.60)	(0.21)	(0.70)	(0.06)	(0.18)	(1.12)	(0.10)	(1.15)	(-0.43)	(-0.30)	(0.83)
Constant	0.0210*	0.0949*	0.0457	0.0225**	0.332***	0.212*	0.272**	0.337***	0.884***	1.010***	0.146	0.879***
	(1.79)	(1.78)	(1.34)	(2.09)	(10.43)	(1.75)	(2.44)	(10.32)	(10.02)	(2.94)	(0.32)	(10.55)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0491	0.184	0.317	0.0510	0.0722	0.356	0.147	0.0718	0.155	0.237	0.0995	0.155
N	17414	700	392	18506	17414	700	392	18506	17414	700	392	18506

C.2.2. Excluding Potentially Endogenous Regressors

Table C.32.:
Bank Liquidity Creation and Managerial Ability, Reduced Set of Regressors.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
MA_{t-1}	0.0691***	0.0863***	-0.00171	0.0622***
	(8.41)	(3.14)	(-0.04)	(7.60)
$BKHHI$	0.0274***	0.0284	-0.0589	0.0238**
	(2.69)	(0.39)	(-0.29)	(2.31)
$BKMSML$	0.0241***	-0.00675	-0.175**	0.0208***
	(4.27)	(-0.21)	(-2.46)	(3.78)
$BKPOP$	0.0151***	0.0358***	0.0309	0.0153***
	(6.98)	(4.00)	(1.60)	(7.44)
$BKPDNS$	0.00652	-0.0200	0.0130	0.00305
	(1.39)	(-1.13)	(0.28)	(0.69)
$BKICHG$	0.158***	0.612***	0.625	0.183***
	(6.84)	(3.95)	(1.20)	(7.95)
$MBHC$	0.0285***	0.0116	0.00233	0.0285***
	(6.29)	(0.55)	(0.07)	(6.54)
$OBHC$	0.0246***	0.0177	0.0149	0.0251***
	(6.94)	(0.87)	(0.46)	(7.15)
MRG	0.0402	0.0487***	0.0499***	0.0457**
	(1.11)	(2.90)	(2.61)	(2.22)
ACQ	-0.00234	0.00153	-0.00265	-0.00247
	(-1.24)	(0.18)	(-0.14)	(-1.33)
Constant	0.0578*	-0.0800	-0.0212	0.0694**
	(1.95)	(-0.58)	(-0.10)	(2.46)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.301	0.289	0.140	0.297
N	79152	3341	1863	84356

Table C.33.: Bank Risk-Taking and Managerial Ability, Reduced Set of Regressors.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using SFA revenue efficiency and standard first stage regressors on a pooled sample. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MA_{t-1}	-0.00177	-0.0161***	-0.00932	-0.00202*	-0.0257***	0.0111	0.00684	-0.0190***	-0.123***	-0.0684**	0.00987	-0.106***
	(-1.51)	(-3.78)	(-1.35)	(-1.81)	(-8.34)	(1.02)	(0.93)	(-6.52)	(-14.75)	(-2.55)	(0.26)	(-13.11)
$BKHHI$	-0.00250**	0.00412	0.0221*	-0.00216*	-0.00435	-0.00123	0.0356	-0.00273	-0.000108	-0.0473	0.0219	0.00222
	(-2.15)	(0.55)	(1.90)	(-1.88)	(-1.58)	(-0.06)	(1.45)	(-0.98)	(-0.02)	(-1.16)	(0.29)	(0.37)
$BKMSML$	-0.00687***	-0.00192	-0.0107	-0.00601***	-0.000268	0.00946	0.0173	0.000374	-0.00698**	-0.00547	0.100**	-0.00451
	(-10.05)	(-0.37)	(-1.51)	(-9.03)	(-0.17)	(1.02)	(1.64)	(0.24)	(-1.97)	(-0.21)	(2.27)	(-1.31)
$BKPOP$	0.00136***	0.000833	0.000202	0.00135***	-0.00412***	-0.00457	-0.000700	-0.00398***	-0.0140***	-0.0123*	-0.00781	-0.0134***
	(5.39)	(0.56)	(0.14)	(5.54)	(-5.70)	(-1.41)	(-0.27)	(-5.88)	(-7.91)	(-1.67)	(-0.63)	(-7.98)
$BKPDNS$	0.00307***	0.00370	-0.00517	0.00299***	-0.00294	0.0163**	0.00176	-0.00111	-0.00547	0.00284	0.0111	-0.00290
	(5.71)	(1.04)	(-1.38)	(5.72)	(-1.55)	(2.31)	(0.26)	(-0.63)	(-1.37)	(0.24)	(0.30)	(-0.78)
$BKICHG$	-0.0232***	-0.0590***	-0.0180	-0.0250***	-0.00630**	-0.0339	-0.0545	-0.00864***	0.0547***	0.000888	-0.119	0.0513***
	(-16.45)	(-4.75)	(-0.68)	(-17.79)	(-2.04)	(-1.45)	(-1.46)	(-2.82)	(7.47)	(0.01)	(-0.82)	(7.06)
$MBHC$	0.00111*	-0.000198	-0.00108	0.000840	-0.0213***	-0.00569	-0.0334*	-0.0211***	-0.0199***	-0.00335	-0.0182	-0.0212***
	(1.95)	(-0.06)	(-0.36)	(1.54)	(-9.83)	(-0.81)	(-1.84)	(-10.34)	(-4.48)	(-0.13)	(-0.61)	(-4.98)
$OBHC$	0.000911*	0.000683	-0.000992	0.000827*	-0.0165***	-0.00678	-0.0340*	-0.0169***	-0.0242***	-0.00885	-0.0231	-0.0252***
	(1.88)	(0.22)	(-0.40)	(1.77)	(-9.21)	(-0.99)	(-1.83)	(-9.73)	(-6.93)	(-0.35)	(-0.84)	(-7.27)
MRG	0.00103	-0.0141***	0.00127	0.00309***	0.0184**	-0.00129	-0.00573**	0.0152	0.00932	-0.00412	-0.0316***	-0.00824
	(0.50)	(-3.04)	(0.94)	(3.75)	(2.24)	(-0.16)	(-2.43)	(1.27)	(0.17)	(-0.22)	(-2.79)	(-0.25)
ACQ	-0.000575**	0.000369	0.000948	-0.000533**	0.00140*	-0.00155	-0.00188	0.00118	0.00309*	-0.0137*	0.000741	0.00298*
	(-2.28)	(0.36)	(0.50)	(-2.21)	(1.74)	(-0.65)	(-0.60)	(1.56)	(1.73)	(-1.83)	(0.06)	(1.71)
Constant	0.00248	0.00956	0.0256	0.00293	0.226***	0.140***	0.131***	0.217***	0.567***	0.534***	0.366***	0.554***
	(0.74)	(0.42)	(1.26)	(0.88)	(21.50)	(3.20)	(3.86)	(22.31)	(23.12)	(4.55)	(2.80)	(23.77)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.266	0.405	0.408	0.274	0.0706	0.0866	0.122	0.0674	0.116	0.141	0.0770	0.112
N	79152	3341	1863	84356	79152	3341	1863	84356	79152	3341	1863	84356

Table C.34.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Reduced Set of Regressors.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0290**	-0.0675	-0.0817	-0.0323***
	(-2.40)	(-1.45)	(-1.30)	(-2.76)
δ_c	0.00103	-0.00372	0.00454	0.000154
	(1.19)	(-1.07)	(0.81)	(0.18)
$BKHHI$	-0.0147	-0.102	-0.518***	-0.0314**
	(-0.98)	(-1.58)	(-4.27)	(-2.10)
$BKMSML$	0.0527***	0.0833*	0.0483	0.0500***
	(6.65)	(1.91)	(0.41)	(6.44)
$BKPOP$	0.00116	0.00561	-0.0627**	-0.00000145
	(0.32)	(0.46)	(-2.06)	(-0.00)
$BKPDNS$	-0.0277***	-0.0378	0.0548	-0.0306***
	(-3.71)	(-1.48)	(0.97)	(-4.21)
$BKICHG$	0.223***	0.803***	0.533**	0.273***
	(9.31)	(6.38)	(2.02)	(11.47)
$MBHC$	0.00680	0.0307	0.0855*	0.0113
	(0.84)	(1.08)	(1.88)	(1.46)
$OBHC$	0.00964	0.0378	0.0686*	0.0120*
	(1.49)	(1.40)	(1.76)	(1.88)
MRG	0	0.0559***	0	0.0472***
	(.)	(3.38)	(.)	(9.39)
ACQ	0.00355	-0.0224	-0.0437	0.00137
	(0.91)	(-0.86)	(-0.95)	(0.34)
Constant	0.335***	0.369**	1.131***	0.367***
	(7.73)	(2.21)	(3.51)	(8.81)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.0290	0.167	0.145	0.0346
N	19890	1059	530	21479

Table C.35.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Reduced Set of Regressors.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0173***	-0.00802	0.00683	-0.0147***	0.000692	0.0253***	0.000390	0.00309	0.0743***	0.0510*	0.00770	0.0663***
	(-5.35)	(-0.72)	(0.72)	(-4.92)	(0.16)	(2.70)	(0.04)	(0.81)	(6.26)	(1.74)	(0.22)	(6.15)
δ_c	0.00670***	0.00919***	0.00724***	0.00714***	-0.00489***	-0.00366***	-0.00664***	-0.00469***	-0.00649***	-0.0137***	-0.0217***	-0.00654***
	(32.79)	(8.66)	(4.84)	(36.21)	(-16.12)	(-3.74)	(-3.64)	(-16.33)	(-8.05)	(-4.92)	(-4.17)	(-8.49)
$BKHHI$	0.00674***	0.0259*	0.0721***	0.00790***	-0.00538**	0.00313	0.0602**	-0.00446*	0.0132**	0.0222	0.0829	0.0161***
	(3.39)	(1.86)	(5.61)	(3.99)	(-2.04)	(0.32)	(2.46)	(-1.70)	(2.08)	(0.94)	(1.29)	(2.60)
$BKMSML$	-0.0195***	-0.0408***	-0.0287	-0.0191***	0.00611***	0.00173	-0.00418	0.00607***	-0.0194***	-0.0165	-0.0556	-0.0193***
	(-17.76)	(-4.67)	(-1.37)	(-17.75)	(4.75)	(0.26)	(-0.27)	(4.86)	(-5.66)	(-0.81)	(-1.08)	(-5.77)
$BKPOP$	0.00303***	0.00225	0.0000461	0.00316***	-0.00350***	0.00119	0.00471	-0.00320***	-0.00252	-0.00830	0.0421**	-0.00188
	(6.33)	(0.57)	(0.01)	(6.63)	(-3.30)	(0.47)	(0.94)	(-3.15)	(-1.18)	(-1.11)	(2.12)	(-0.91)
$BKPDNS$	0.00396***	0.00889	0.00924	0.00457***	-0.00147	0.00623	-0.00483	-0.00102	0.00262	-0.00934	-0.0594*	0.00260
	(3.38)	(0.93)	(1.10)	(3.90)	(-0.87)	(1.08)	(-0.47)	(-0.63)	(0.61)	(-0.78)	(-1.89)	(0.63)
$BKICHG$	-0.0276***	-0.0797***	-0.0905***	-0.0327***	-0.00512**	-0.0567***	-0.103***	-0.00889***	-0.0790***	-0.297***	-0.293***	-0.0904***
	(-15.46)	(-6.05)	(-3.30)	(-18.07)	(-2.21)	(-4.89)	(-5.14)	(-3.94)	(-12.49)	(-7.59)	(-3.78)	(-14.28)
$MBHC$	0.00585***	-0.00978*	-0.0135	0.00345*	-0.0139***	-0.00496	-0.0814***	-0.0160***	-0.00938	-0.0316	-0.0498	-0.0135*
	(2.96)	(-1.67)	(-1.26)	(1.77)	(-3.82)	(-0.78)	(-3.06)	(-4.55)	(-1.12)	(-1.50)	(-1.35)	(-1.70)
$OBHC$	0.00576***	-0.00456	-0.00780	0.00472***	-0.0112***	-0.00251	-0.0813***	-0.0130***	-0.0206***	-0.0404**	-0.0557*	-0.0221***
	(3.46)	(-0.91)	(-1.06)	(2.94)	(-3.37)	(-0.41)	(-3.09)	(-3.93)	(-2.92)	(-2.12)	(-1.81)	(-3.25)
MRG	0	-0.0144	0	-0.00609***	0	-0.000651	0	0.0211***	0	0.00800	0	-0.00975*
	(.)	(-1.13)	(.)	(-3.86)	(.)	(-0.08)	(.)	(8.04)	(.)	(0.42)	(.)	(-1.72)
ACQ	-0.00374***	0.000447	0.00685	-0.00325***	-0.000596	0.00188	0.00540	-0.000218	0.00231	0.00408	0.0289	0.00345
	(-3.41)	(0.10)	(1.02)	(-3.10)	(-0.46)	(0.33)	(0.88)	(-0.17)	(0.60)	(0.22)	(1.00)	(0.91)
Constant	-0.0304***	-0.0127	0.00359	-0.0333***	0.207***	0.0799*	0.134**	0.202***	0.375***	0.485***	0.0119	0.367***
	(-5.03)	(-0.20)	(0.04)	(-5.47)	(15.31)	(1.92)	(2.08)	(15.31)	(14.45)	(4.37)	(0.04)	(14.48)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.192	0.394	0.349	0.202	0.0405	0.0538	0.290	0.0382	0.0280	0.162	0.137	0.0309
N	19890	1059	530	21479	19890	1059	530	21479	19890	1059	530	21479

C.2.3. Including the Equity over Asset Ratio as a Regressor

Table C.36.: Bank Liquidity Creation and Managerial Ability, Regressors Include EA.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the equity over asset ratio (EA) and log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
MA_{t-1}	0.0137**	0.0518**	-0.0220	0.0138**
	(2.03)	(2.34)	(-0.63)	(2.05)
EA	-0.550***	-0.203	-0.0249	-0.511***
	(-14.69)	(-1.23)	(-0.09)	(-14.17)
$CREDRSK$	0.620***	0.678***	0.826***	0.628***
	(56.12)	(14.33)	(11.00)	(58.37)
$ZIND$	-0.000821**	-0.00207	0.00147	-0.000687**
	(-2.42)	(-1.54)	(0.59)	(-2.11)
$SDROA$	-0.00803***	-0.0319***	-0.0324**	-0.00967***
	(-3.57)	(-4.21)	(-2.06)	(-4.52)
$BKSIZE$	-0.0164***	-0.0157	0.00300	-0.0151***
	(-6.38)	(-1.43)	(0.22)	(-6.57)
$BKHHI$	0.0156**	-0.0253	0.0165	0.0128
	(1.98)	(-0.45)	(0.10)	(1.59)
$BKMSML$	0.0207***	-0.00385	-0.0934	0.0195***
	(4.68)	(-0.14)	(-1.62)	(4.54)
$BKPOP$	0.00775***	0.0229***	0.0255	0.00834***
	(4.71)	(2.71)	(1.43)	(5.26)
$BKPDNS$	0.00113	-0.0166	-0.0108	-0.000680
	(0.32)	(-1.20)	(-0.28)	(-0.20)
$BKICHG$	0.187***	0.540***	0.653**	0.207***
	(10.05)	(4.49)	(2.06)	(11.17)
$MBHC$	0.0176***	0.0129	0.0285	0.0175***

Continued on next page

Table C.36 – *Continued from previous page*

	Small	Medium	Large	Full
	(4.84)	(0.78)	(0.66)	(5.06)
OBHC	0.0129***	0.0192	0.0364	0.0135***
	(4.51)	(1.22)	(0.86)	(4.82)
MRG	0.0288***	0.0796***	0.0292*	0.0618***
	(6.61)	(4.82)	(1.88)	(7.28)
ACQ	0.000674	0.00422	-0.00768	0.000484
	(0.44)	(0.57)	(-0.61)	(0.32)
Constant	-0.000205	-0.144	-0.392	-0.0208
	(-0.01)	(-0.73)	(-1.40)	(-0.66)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.480	0.461	0.375	0.477
N	79152	3341	1863	84356

Table C.37.: Bank Risk-Taking and Managerial Ability, Regressors Include EA.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the equity over asset ratio (EA) and log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MA_{t-1}	-0.00169	-0.0123***	-0.00289	-0.00153	-0.00647***	0.0137**	-0.000743	-0.00804***	-0.0688***	-0.0448**	-0.00495	-0.0603***
	(-1.51)	(-3.15)	(-0.49)	(-1.43)	(-4.57)	(2.18)	(-0.13)	(-5.37)	(-12.24)	(-2.18)	(-0.17)	(-11.05)
EA	-0.0322***	-0.0159	-0.0208	-0.0302***	1.270***	0.711***	0.470***	1.192***	0.180***	0.151*	0.0814	0.192***
	(-6.25)	(-0.67)	(-1.04)	(-6.37)	(75.88)	(7.68)	(6.81)	(67.26)	(7.14)	(1.74)	(0.70)	(8.21)
$CREDRSK$	0.0109***	-0.000631	0.0127	0.0100***	-0.237***	-0.141***	-0.105***	-0.230***	-0.727***	-0.756***	-0.706***	-0.731***
	(10.52)	(-0.11)	(1.54)	(9.85)	(-94.29)	(-11.37)	(-10.06)	(-90.30)	(-69.20)	(-22.87)	(-18.43)	(-73.09)
$ZIND$	-0.000249***	-0.000177	-0.000502**	-0.000231***	0.000320***	0.000561*	-0.0000300	0.000370***	0.0000933	0.00104*	0.000363	0.0000822
	(-7.88)	(-1.26)	(-2.35)	(-7.62)	(5.83)	(1.95)	(-0.08)	(6.59)	(0.56)	(1.84)	(0.42)	(0.51)
$SDROA$	0.0118***	0.0120***	0.0132***	0.0121***	-0.00288***	0.000845	0.00243*	-0.00271***	0.00212**	0.00263	-0.000838	0.00236**
	(26.96)	(8.46)	(7.98)	(29.93)	(-7.96)	(0.55)	(1.70)	(-7.53)	(1.98)	(0.75)	(-0.14)	(2.38)
$BKSIZE$	0.00110***	0.00222	0.000634	0.00153***	-0.00529***	-0.0185***	-0.0138***	-0.00739***	-0.00406**	0.00272	0.0271**	-0.00174
	(2.86)	(1.11)	(0.25)	(4.55)	(-6.46)	(-4.14)	(-3.91)	(-9.66)	(-2.02)	(0.29)	(2.37)	(-0.99)
$BKHHI$	-0.000615	-0.00104	0.0114	-0.000491	-0.00219*	-0.000949	0.0139	-0.00233*	0.00522	-0.0329	-0.0423	0.00543
	(-0.58)	(-0.15)	(1.39)	(-0.48)	(-1.68)	(-0.07)	(1.28)	(-1.74)	(1.21)	(-1.39)	(-0.79)	(1.28)
$BKMSML$	-0.00626***	0.00417	-0.00540	-0.00547***	-0.00130*	0.00947	0.0112	-0.00148*	-0.00200	0.00620	0.0284	-0.000729
	(-9.97)	(0.90)	(-0.82)	(-9.00)	(-1.72)	(1.29)	(1.34)	(-1.94)	(-0.79)	(0.35)	(0.74)	(-0.30)
$BKPOP$	0.00115***	-0.000186	-0.000964	0.00106***	0.0000649	-0.00304	-0.00451*	-0.000139	-0.00564***	-0.00175	-0.00449	-0.00567***
	(5.04)	(-0.14)	(-0.74)	(4.75)	(0.19)	(-1.20)	(-1.84)	(-0.38)	(-5.15)	(-0.36)	(-0.40)	(-5.35)
$BKPDNS$	0.00266***	0.00373	-0.00514*	0.00244***	-0.00153*	0.00904**	0.00658	-0.00106	-0.00117	-0.00560	0.00932	-0.000353
	(5.23)	(1.28)	(-1.74)	(5.01)	(-1.70)	(2.01)	(1.36)	(-1.15)	(-0.47)	(-0.72)	(0.32)	(-0.15)
$BKICHG$	-0.0224***	-0.0439***	0.00797	-0.0236***	-0.00694***	-0.0313*	-0.0728***	-0.00882***	0.0184***	0.0508	-0.0479	0.0177***
	(-16.69)	(-3.84)	(0.38)	(-17.82)	(-4.35)	(-1.88)	(-3.00)	(-5.40)	(3.59)	(1.17)	(-0.57)	(3.49)
$MBHC$	0.000993*	-0.000766	-0.000401	0.000753	-0.0140***	-0.00225	-0.0352**	-0.0134***	-0.00675**	0.00211	-0.0320**	-0.00736***
	(1.86)	(-0.23)	(-0.16)	(1.47)	(-11.61)	(-0.44)	(-2.36)	(-11.40)	(-2.26)	(0.17)	(-2.26)	(-2.59)
$OBHC$	0.000358	-0.000238	-0.000748	0.000202	-0.00242***	0.00125	-0.0319**	-0.00275***	-0.00838***	-0.00398	-0.0304**	-0.00927***
	(0.78)	(-0.08)	(-0.38)	(0.46)	(-2.74)	(0.28)	(-2.15)	(-3.04)	(-3.38)	(-0.34)	(-2.30)	(-3.83)

Continued on next page

Table C.37 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MRG	0.00449**	-0.0114***	-0.000158	0.00372***	-0.0516	0.00551	0.000646	-0.0182	-0.0243	0.00418	0.00847	-0.0122
	(2.15)	(-3.00)	(-0.12)	(5.16)	(-1.15)	(0.90)	(0.33)	(-1.28)	(-0.74)	(0.30)	(0.90)	(-1.14)
ACQ	-0.000346	0.00140	0.000556	-0.000254	-0.00360***	-0.00576***	-0.00409	-0.00392***	0.0000936	-0.0151***	0.00424	-0.000303
	(-1.44)	(1.35)	(0.33)	(-1.11)	(-7.21)	(-2.61)	(-1.63)	(-7.67)	(0.07)	(-2.74)	(0.56)	(-0.25)
Constant	-0.0108**	-0.0117	0.0208	-0.0140***	0.253***	0.434***	0.430***	0.283***	0.954***	0.869***	0.473**	0.929***
	(-2.08)	(-0.38)	(0.47)	(-3.00)	(26.84)	(6.24)	(6.28)	(29.34)	(36.35)	(5.32)	(2.33)	(38.91)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.321	0.505	0.514	0.335	0.751	0.533	0.452	0.723	0.532	0.585	0.459	0.532
N	79152	3341	1863	84356	79152	3341	1863	84356	79152	3341	1863	84356

Table C.38.:

Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Regressors Include EA.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the equity over asset ratio (EA) and the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	0.00684	-0.0558	-0.0715*	-0.00700
	(0.59)	(-1.36)	(-1.66)	(-0.63)
δ_c	-0.00464***	-0.00714*	-0.0108	-0.00590***
	(-5.23)	(-1.77)	(-1.54)	(-6.90)
EA	-0.299***	-0.314	0.0961	-0.278***
	(-3.20)	(-0.89)	(0.14)	(-3.13)
$CREDRSK$	0.774***	0.734***	0.769***	0.779***
	(29.87)	(7.01)	(4.28)	(31.10)
$ZIND$	0.00169***	0.00212	0.00549	0.00161***
	(2.80)	(0.77)	(1.06)	(2.76)
$SDROA$	-0.0254***	-0.0362***	-0.0317**	-0.0263***
	(-6.65)	(-4.13)	(-1.98)	(-7.63)
$BKSIZE$	-0.0682***	-0.0252	-0.0198	-0.0567***
	(-9.36)	(-1.03)	(-1.15)	(-9.04)
$BKHHI$	-0.00211	-0.134**	-0.411***	-0.0179
	(-0.17)	(-2.42)	(-3.78)	(-1.46)
$BKMSML$	0.0351***	0.106***	0.0697	0.0370***
	(5.26)	(2.65)	(0.60)	(5.71)
$BKPOP$	0.00352	0.00635	-0.0235	0.00263
	(1.19)	(0.57)	(-0.66)	(0.93)
$BKPDNS$	-0.0209***	-0.0429*	-0.00377	-0.0245***
	(-3.30)	(-1.71)	(-0.06)	(-3.97)
$BKICHG$	0.208***	0.551***	0.400	0.245***
	(9.87)	(4.32)	(1.46)	(11.83)

Continued on next page

Table C.38 – *Continued from previous page*

Parameter	Small	Medium	Large	Full
MBHC	0.000298	0.0215	0.0599	0.00130
	(0.04)	(0.92)	(1.45)	(0.19)
OBHC	0.00200	0.0320	0.0403	0.00269
	(0.34)	(1.43)	(1.22)	(0.47)
MRG	0	0.0817***	0	0.0919***
	(.)	(4.58)	(.)	(15.66)
ACQ	0.00649*	-0.0227	-0.0318	0.00511
	(1.92)	(-1.08)	(-0.90)	(1.51)
Constant	0.592***	0.211	0.488	0.491***
	(6.49)	(0.67)	(1.07)	(6.13)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.226	0.311	0.316	0.232
N	19793	1059	529	21381

Table C.39.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Regressors Include EA.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c)and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the equity over asset ratio (EA) and the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0159***	-0.00832	0.00903	-0.0136***	0.00295	0.0144**	-0.0118	0.000822	0.0250***	0.0114	-0.0247	0.0173**
	(-5.44)	(-0.82)	(0.99)	(-5.01)	(1.30)	(1.97)	(-1.22)	(0.35)	(2.91)	(0.58)	(-0.73)	(2.14)
δ_c	0.00684***	0.00909***	0.00803***	0.00720***	-0.00215***	-0.00172**	-0.00347**	-0.00215***	0.000891	-0.00603***	-0.00389	0.000338
	(31.61)	(8.74)	(5.44)	(34.75)	(-10.79)	(-2.34)	(-2.41)	(-11.45)	(1.39)	(-2.74)	(-1.12)	(0.58)
EA	-0.0674***	-0.0400	-0.0928*	-0.0574***	0.946***	0.590***	0.451***	0.903***	-0.139***	0.105	-0.247	-0.137***
	(-4.59)	(-0.57)	(-1.97)	(-4.15)	(29.20)	(6.13)	(3.62)	(28.59)	(-2.87)	(0.89)	(-0.74)	(-2.99)
$CREDRSK$	0.00544	-0.0246	-0.00105	-0.000152	-0.195***	-0.110***	-0.0963***	-0.186***	-0.803***	-0.618***	-0.660***	-0.790***
	(1.63)	(-1.49)	(-0.04)	(-0.05)	(-39.62)	(-8.11)	(-4.21)	(-38.39)	(-41.91)	(-10.83)	(-8.18)	(-44.89)
$ZIND$	0.000294***	0.000222	-0.000429	0.000383***	0.0000721	0.000666	-0.000191	0.000135	-0.000545**	0.000660	-0.00156	-0.000691***
	(3.38)	(0.70)	(-0.60)	(4.56)	(0.79)	(1.07)	(-0.44)	(1.44)	(-2.36)	(0.91)	(-0.99)	(-3.16)
$SDROA$	0.0138***	0.0113***	0.0108***	0.0138***	-0.00459***	0.000595	0.00185	-0.00319***	0.00266*	0.00408	-0.00129	0.00206*
	(20.38)	(6.15)	(6.08)	(22.91)	(-7.18)	(0.37)	(0.99)	(-5.36)	(1.94)	(1.15)	(-0.29)	(1.71)
$BKSIZE$	-0.000999	0.00804	-0.00965	-0.0000338	-0.0258***	-0.0162***	-0.00642	-0.0232***	-0.00418	0.0101	0.0193*	-0.00117
	(-0.67)	(1.21)	(-1.47)	(-0.02)	(-11.96)	(-2.83)	(-1.65)	(-12.35)	(-0.64)	(0.62)	(1.72)	(-0.23)
$BKHHI$	0.00840***	0.0170	0.0584***	0.00889***	-0.00157	0.00931	0.0171	-0.00170	0.00719*	-0.00396	-0.0459	0.00605
	(4.76)	(1.27)	(4.41)	(5.09)	(-1.14)	(1.00)	(1.29)	(-1.20)	(1.68)	(-0.22)	(-0.96)	(1.44)
$BKMSML$	-0.0180***	-0.0249***	-0.0273	-0.0172***	0.00117	-0.00347	-0.000948	0.00184**	0.00261	0.0274*	-0.00393	0.00272
	(-18.10)	(-3.35)	(-1.52)	(-17.81)	(1.61)	(-0.51)	(-0.09)	(2.48)	(1.10)	(1.72)	(-0.11)	(1.20)
$BKPOP$	0.00299***	0.000954	-0.000832	0.00299***	-0.000298	0.000517	-0.00146	-0.000504	-0.00200*	-0.00584	0.0144	-0.00225*
	(6.50)	(0.27)	(-0.17)	(6.58)	(-0.60)	(0.27)	(-0.30)	(-0.99)	(-1.65)	(-1.13)	(0.79)	(-1.91)
$BKPDNS$	0.00287***	0.00856	0.00363	0.00337***	-0.0000598	0.00293	0.00526	0.0000558	-0.00124	-0.0221**	-0.0346	-0.00255
	(2.79)	(1.03)	(0.55)	(3.32)	(-0.08)	(0.89)	(0.58)	(0.07)	(-0.45)	(-2.21)	(-1.18)	(-0.96)
$BKICHG$	-0.0307***	-0.0624***	-0.0642**	-0.0340***	-0.00000421	-0.0274***	-0.0503***	-0.000991	-0.0261***	-0.125***	-0.0582	-0.0245***
	(-17.34)	(-5.19)	(-2.11)	(-19.44)	(-0.00)	(-3.48)	(-2.76)	(-0.72)	(-5.56)	(-3.77)	(-1.00)	(-5.34)
$MBHC$	0.00559***	-0.0197***	-0.00997	0.00336*	-0.00830***	0.0169**	-0.0591***	-0.00769***	-0.00546	-0.0251**	-0.0304	-0.00691

Continued on next page

Table C.39 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(3.09)	(-3.24)	(-0.88)	(1.88)	(-2.70)	(2.14)	(-2.65)	(-2.63)	(-0.94)	(-2.05)	(-0.98)	(-1.26)
OBHC	0.00443***	-0.0159***	-0.00560	0.00347**	0.00184	0.0201**	-0.0583***	0.000682	-0.00844*	-0.0271**	-0.0316	-0.00951**
	(2.85)	(-3.13)	(-0.71)	(2.32)	(0.75)	(2.58)	(-2.65)	(0.28)	(-1.68)	(-2.46)	(-1.14)	(-1.97)
MRG	0	-0.0147	0	-0.00527***	0	0.00761	0	0.0205***	0	0.0250	0	0.00680
	(.)	(-1.34)	(.)	(-3.32)	(.)	(1.60)	(.)	(9.95)	(.)	(1.61)	(.)	(1.42)
ACQ	-0.00270***	0.00504	0.00761	-0.00202**	-0.00633***	-0.0115	-0.00310	-0.00653***	0.00121	-0.00203	0.00898	0.00134
	(-2.78)	(1.33)	(1.08)	(-2.17)	(-4.89)	(-1.44)	(-0.44)	(-5.07)	(0.46)	(-0.24)	(0.67)	(0.54)
Constant	-0.0115	-0.0861	0.192*	-0.0211	0.496***	0.339***	0.297***	0.469***	0.983***	0.765***	0.501	0.948***
	(-0.64)	(-0.83)	(1.77)	(-1.26)	(17.12)	(4.40)	(3.35)	(18.30)	(11.98)	(3.35)	(1.54)	(14.27)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.287	0.504	0.448	0.304	0.668	0.461	0.538	0.636	0.563	0.565	0.559	0.565
N	19793	1059	529	21381	19793	1059	529	21381	19793	1059	529	21381

C.2.4. Reduced Sample Period

Table C.40.: Bank Liquidity Creation and Managerial Ability, Sample Ends 2006.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
MA_{t-1}	0.0124*	0.0477	0.0543	0.0114*
	(1.83)	(1.42)	(1.34)	(1.68)
$CREDRSK$	0.644***	0.831***	0.867***	0.656***
	(52.82)	(21.01)	(17.54)	(55.56)
$ZIND$	-0.000406**	-0.000328	0.00140	-0.000342**
	(-2.28)	(-0.48)	(1.17)	(-1.96)
$SDROA$	0.000514	-0.0229**	-0.0113	-0.000582
	(0.29)	(-2.35)	(-0.75)	(-0.34)
$BKSIZE$	0.00764***	-0.0258**	0.00786	0.00408*
	(3.02)	(-2.04)	(0.52)	(1.77)
$BKHHI$	0.00804	-0.00192	0.0752	0.00799
	(1.41)	(-0.05)	(0.96)	(1.35)
$BKMSML$	0.00271	0.0109	-0.0464	0.00204
	(0.76)	(0.43)	(-1.00)	(0.58)
$BKPOP$	0.0108***	0.0150**	0.0359***	0.0116***
	(6.69)	(2.30)	(3.02)	(7.56)
$BKPDNS$	0.0101***	-0.0177	-0.0374	0.00722**
	(2.78)	(-1.60)	(-1.13)	(2.06)
$BKICHG$	0.00377	0.0679	-0.0282	0.00511
	(0.56)	(1.06)	(-0.24)	(0.77)
$MBHC$	0.0183***	-0.00228	0.0306	0.0172***
	(5.09)	(-0.17)	(1.31)	(5.01)
$OBHC$	0.0114***	-0.000717	0.0427*	0.0116***
	(3.98)	(-0.06)	(1.85)	(4.18)

Continued on next page

Table C.40 – *Continued from previous page*

	Small	Medium	Large	Full
MRG	0.0644***		-0.0282**	0.0450***
	(3.01)		(-2.13)	(2.88)
ACQ	-0.0000832	0.00695	-0.00821	0.0000337
	(-0.06)	(1.15)	(-0.74)	(0.02)
Constant	-0.400***	0.00996	-0.753***	-0.365***
	(-11.92)	(0.05)	(-2.78)	(-11.63)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.587	0.658	0.533	0.588
N	59463	2281	1418	63162

Table C.41.: Bank Risk-Taking and Managerial Ability, Sample Ends 2006.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MA_{t-1}	0.00155	-0.0000779	-0.00802**	0.000488	-0.00868***	-0.000515	0.00611	-0.00685**	-0.0684***	-0.0584	0.0241	-0.0563***
	(1.56)	(-0.03)	(-2.36)	(0.54)	(-2.97)	(-0.05)	(1.10)	(-2.47)	(-8.97)	(-1.57)	(0.51)	(-7.34)
$CREDRSK$	0.00920***	0.0106***	0.00681*	0.00911***	-0.193***	-0.0724***	-0.0547***	-0.187***	-0.559***	-0.541***	-0.530***	-0.559***
	(8.91)	(3.12)	(1.67)	(9.22)	(-40.26)	(-4.99)	(-2.89)	(-40.27)	(-46.33)	(-9.22)	(-8.38)	(-48.20)
zindmo33w	-0.000133***	0.0000446	-0.000212	-0.000121***	0.000309*	0.000126	0.000444	0.000246	0.000575	0.00126	0.00301*	0.000427
	(-2.87)	(0.22)	(-1.19)	(-2.69)	(1.75)	(0.25)	(0.69)	(1.47)	(1.57)	(0.80)	(1.66)	(1.22)
$SDROA$	0.00380***	0.00334	0.00809***	0.00378***	-0.000183	0.0208**	0.0172**	0.00110	0.00696**	0.0501***	-0.0150	0.00895***
	(8.11)	(1.61)	(2.86)	(8.35)	(-0.13)	(2.36)	(2.49)	(0.80)	(2.19)	(3.35)	(-0.39)	(2.84)
$BKSIZE$	0.0000281	0.00145	-0.000154	-0.000371	-0.00548***	-0.000404	-0.00640**	-0.00374***	0.00433	-0.00108	0.0306**	0.00802***
	(0.09)	(1.36)	(-0.15)	(-1.36)	(-4.12)	(-0.10)	(-2.43)	(-3.24)	(1.58)	(-0.09)	(2.02)	(3.25)
$BKHHI$	-0.00325**	-0.000161	0.0159	-0.00350**	-0.00540	0.0160	-0.0295	-0.00526	-0.00316	-0.0472	-0.379**	0.00181
	(-2.01)	(-0.03)	(1.32)	(-2.20)	(-0.91)	(0.33)	(-1.00)	(-0.88)	(-0.30)	(-0.53)	(-2.24)	(0.17)
$BKMSML$	0.00106	-0.000270	-0.0135***	0.000493	0.00129	0.0175	0.0381***	0.00161	-0.0155**	-0.0223	0.0683	-0.0136**
	(1.31)	(-0.10)	(-3.54)	(0.64)	(0.44)	(1.10)	(3.27)	(0.58)	(-2.55)	(-0.74)	(1.37)	(-2.34)
$BKPOP$	0.000325	-0.00237***	0.000172	0.000244	-0.00106	-0.00141	-0.00369	-0.00131	-0.00843***	-0.00112	-0.00986	-0.00813***
	(1.28)	(-3.17)	(0.16)	(1.01)	(-1.19)	(-0.39)	(-1.36)	(-1.58)	(-4.29)	(-0.09)	(-0.77)	(-4.32)
$BKPDNS$	-0.000343	0.00150	-0.00304	-0.000523	-0.00114	0.00602	-0.00136	0.000118	-0.00212	0.00326	0.0174	0.00213
	(-0.61)	(1.16)	(-1.20)	(-1.00)	(-0.43)	(0.99)	(-0.22)	(0.05)	(-0.44)	(0.19)	(0.57)	(0.47)
$BKICHG$	-0.0123***	-0.0165	-0.0341	-0.0120***	-0.0399***	-0.0509	0.0573	-0.0399***	0.0592***	-0.189	0.167	0.0559***
	(-4.22)	(-1.09)	(-1.61)	(-4.22)	(-4.50)	(-0.71)	(1.01)	(-4.57)	(3.00)	(-1.17)	(0.52)	(2.86)
$MBHC$	-0.000573	0.00278	-0.00214	-0.000520	-0.0180***	-0.00381	-0.0129*	-0.0179***	-0.00919**	-0.0108	-0.0286	-0.0102***
	(-1.32)	(1.04)	(-0.76)	(-1.27)	(-8.90)	(-0.81)	(-1.91)	(-9.41)	(-2.51)	(-0.62)	(-0.70)	(-2.89)
$OBHC$	-0.000805**	0.00264	-0.00266	-0.000741**	-0.0114***	-0.00418	-0.0130**	-0.0121***	-0.0115***	-0.0157	-0.0402	-0.0132***
	(-2.14)	(0.99)	(-0.93)	(-2.04)	(-6.82)	(-0.94)	(-2.05)	(-7.48)	(-3.86)	(-0.95)	(-1.02)	(-4.50)
MRG	0.000160		0.000159	0.00139	0.0267***		-0.00232	0.00720	0.0299		-0.0101	-0.0253
	(0.11)		(0.17)	(1.48)	(8.37)		(-1.12)	(0.70)	(0.70)		(-0.73)	(-0.72)

Continued on next page

Table C.41 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
ACQ	-0.00000587	0.00202***	0.00166**	0.0000810	0.000813	0.000340	0.00210	0.000833	0.00143	-0.0149**	0.00950	0.00150
	(-0.03)	(3.78)	(2.08)	(0.42)	(1.09)	(0.16)	(0.79)	(1.18)	(0.93)	(-2.04)	(0.87)	(1.01)
Constant	0.00595	0.00810	0.0245	0.0122***	0.376***	0.163**	0.289***	0.350***	0.786***	0.780***	0.412	0.727***
	(1.34)	(0.49)	(1.24)	(3.03)	(21.27)	(2.51)	(6.51)	(22.28)	(21.94)	(3.04)	(1.43)	(21.65)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.274	0.272	0.464	0.272	0.213	0.0986	0.105	0.204	0.304	0.264	0.229	0.296
N	59463	2281	1418	63162	59463	2281	1418	63162	59463	2281	1418	63162

C.2.5. Alternative Crisis Period

C.2.5.1. Crisis 2008-2009

Table C.42.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Crisis Defined as 2008-2009.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	0.0244**	-0.00338	-0.00777	0.0193*
	(1.98)	(-0.07)	(-0.14)	(1.65)
δ_c	-0.0000278	-0.00655	-0.0158*	-0.000814
	(-0.03)	(-1.21)	(-1.71)	(-0.85)
$CREDRSK$	0.750***	0.672***	0.860***	0.751***
	(36.21)	(9.55)	(8.80)	(38.68)
$ZIND$	0.000557	-0.000539	0.00312	0.000369
	(1.36)	(-0.32)	(0.89)	(0.94)
$SDROA$	-0.00829***	-0.0148***	-0.00916	-0.00840***
	(-4.95)	(-3.32)	(-1.40)	(-5.41)
$BKSIZE$	-0.0126*	-0.0680***	-0.0106	-0.0114**
	(-1.94)	(-2.78)	(-0.57)	(-2.01)
$BKHHI$	-0.0144***	-0.0444	-0.0847	-0.0170***
	(-2.65)	(-1.46)	(-1.28)	(-3.19)
$BKMSML$	0.0101***	0.0150	0.00671	0.00939***
	(2.99)	(0.61)	(0.11)	(2.87)
$BKPOP$	0.00433**	0.0142**	-0.0261	0.00442***
	(2.47)	(2.00)	(-1.06)	(2.61)
$BKPDNS$	-0.0130***	0.00951	0.00751	-0.0134***

Continued on next page

Table C.42 – *Continued from previous page*

	Small	Medium	Large	Full
	(-3.41)	(0.67)	(0.22)	(-3.65)
$BKICHG$	0.00965*	-0.00199	-0.155	0.00897
	(1.67)	(-0.05)	(-1.52)	(1.58)
$MBHC$	0.00166	0.0412	0.0329	0.00295
	(0.23)	(1.65)	(1.08)	(0.43)
$OBHC$	-0.00198	0.0494**	0.0154	-0.000135
	(-0.34)	(2.06)	(0.63)	(-0.02)
MRG	0	0.0487**	0	0.0438***
	(.)	(1.99)	(.)	(7.16)
ACQ	0.00494	-0.0210	-0.0139	0.00318
	(1.45)	(-0.94)	(-0.47)	(0.94)
Constant	-0.0840	0.617*	0.322	-0.0913
	(-1.05)	(1.72)	(0.70)	(-1.27)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.467	0.508	0.586	0.473
N	14785	795	379	15959

Table C.43.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Crisis Defined as 2008-2009.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0244***	-0.00983	0.0308*	-0.0178***	0.00742	0.0222*	-0.00699	0.00795*	0.0283**	0.0434	0.0347	0.0301**
	(-6.29)	(-0.76)	(1.92)	(-4.84)	(1.48)	(1.91)	(-0.49)	(1.76)	(2.15)	(1.58)	(0.62)	(2.49)
δ_c	0.00877***	0.0165***	0.0166***	0.00980***	-0.00187***	0.00141	-0.00102	-0.00161***	0.00883***	0.00519	0.00440	0.00920***
	(25.67)	(8.25)	(6.50)	(30.08)	(-3.99)	(0.85)	(-0.36)	(-3.74)	(7.48)	(1.23)	(0.64)	(8.35)
$CREDRSK$	0.0463***	0.0193	0.0597	0.0448***	-0.205***	-0.111***	-0.122***	-0.201***	-0.847***	-0.811***	-0.869***	-0.858***
	(8.04)	(0.61)	(1.32)	(7.99)	(-20.84)	(-3.62)	(-3.39)	(-21.62)	(-32.99)	(-9.40)	(-6.10)	(-35.03)
$ZIND$	-0.000734***	-0.000685	0.0000444	-0.000644***	-0.000342	-0.00175*	-0.00219*	-0.000383	-0.000490	0.00176	0.00380	-0.000112
	(-3.97)	(-0.98)	(0.03)	(-3.59)	(-1.20)	(-1.77)	(-1.94)	(-1.43)	(-0.77)	(0.65)	(0.88)	(-0.18)
$SDROA$	0.0244***	0.0271***	0.0310***	0.0250***	-0.0178***	-0.00771	-0.00592	-0.0153***	0.0230***	0.00579	0.00450	0.0207***
	(16.30)	(7.05)	(5.62)	(18.38)	(-11.41)	(-1.63)	(-1.01)	(-10.31)	(6.52)	(0.70)	(0.33)	(6.63)
$BKSIZE$	0.0205***	0.00477	-0.00187	0.0160***	-0.0181***	-0.0111*	-0.00135	-0.0143***	0.0190***	-0.0156	0.0225	0.0181***
	(10.08)	(0.64)	(-0.27)	(9.20)	(-6.33)	(-1.74)	(-0.26)	(-6.34)	(2.63)	(-1.10)	(1.49)	(3.08)
$BKHHI$	0.00257	-0.0369	-0.00899	0.00281	-0.00530	-0.00732	0.100**	-0.00134	0.0291**	0.0448	0.0772	0.0346***
	(0.65)	(-1.53)	(-0.42)	(0.73)	(-1.02)	(-0.35)	(2.11)	(-0.25)	(2.25)	(0.80)	(0.76)	(2.76)
$BKMSML$	-0.0108***	0.0180	0.0122	-0.00907***	-0.00178	0.000935	-0.0171	0.00209	-0.0423***	0.0363	-0.0590	-0.0398***
	(-4.61)	(1.14)	(0.27)	(-3.98)	(-0.64)	(0.06)	(-0.51)	(0.78)	(-5.74)	(1.03)	(-0.48)	(-5.67)
$BKPOP$	0.00325***	0.00478	0.00401	0.00357***	-0.0000906	0.00398	0.00593	-0.0000957	0.00199	-0.00596	0.0382	0.00215
	(3.80)	(0.89)	(0.54)	(4.32)	(-0.07)	(1.12)	(0.70)	(-0.08)	(0.71)	(-0.60)	(1.12)	(0.82)
$BKPDNS$	0.00329*	0.00907	-0.0258**	0.00368**	-0.000501	0.00757	0.00763	0.000533	0.000932	0.01000	-0.0561	0.00222
	(1.93)	(0.77)	(-2.22)	(2.19)	(-0.21)	(0.76)	(0.44)	(0.23)	(0.14)	(0.51)	(-1.02)	(0.35)
$BKICHG$	-0.107***	-0.204***	-0.169**	-0.123***	-0.0443***	-0.151***	-0.222***	-0.0573***	-0.134***	-0.731***	-0.509**	-0.161***
	(-16.68)	(-6.22)	(-2.06)	(-19.91)	(-5.35)	(-3.84)	(-3.70)	(-7.19)	(-6.33)	(-7.74)	(-2.21)	(-7.97)
$MBHC$	0.00393*	-0.0281***	-0.00725	0.00265	-0.0106***	-0.00347	-0.0596**	-0.0133***	-0.00629	-0.0418**	0.00286	-0.00773
	(1.74)	(-3.66)	(-0.75)	(1.21)	(-2.72)	(-0.43)	(-2.00)	(-3.54)	(-0.71)	(-1.97)	(0.10)	(-0.93)
$OBHC$	0.00267	-0.0264***	-0.00679	0.00180	-0.00651*	0.00117	-0.0600**	-0.00878**	-0.0118	-0.0448**	-0.00995	-0.0127*

Continued on next page

Table C.43 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(1.40)	(-4.21)	(-1.13)	(0.98)	(-1.89)	(0.15)	(-2.05)	(-2.57)	(-1.57)	(-2.25)	(-0.42)	(-1.77)
MRG	0	-0.0120	0	-0.00390**	0	0.0102	0	0.0246***	0	-0.00476	0	-0.0164***
	(.)	(-1.13)	(.)	(-2.24)	(.)	(1.63)	(.)	(10.84)	(.)	(-0.29)	(.)	(-2.95)
ACQ	-0.00404***	0.00865*	0.00754	-0.00337***	-0.0000890	-0.00306	0.00602	0.0000440	0.000240	-0.00195	0.0124	0.000462
	(-3.52)	(1.65)	(1.31)	(-3.06)	(-0.06)	(-0.44)	(0.62)	(0.03)	(0.06)	(-0.11)	(0.44)	(0.13)
Constant	-0.298***	-0.139	0.0290	-0.253***	0.516***	0.280***	0.170	0.468***	0.688***	1.212***	0.320	0.699***
	(-11.90)	(-1.02)	(0.32)	(-11.42)	(14.38)	(2.75)	(1.60)	(15.52)	(7.86)	(4.97)	(0.74)	(9.36)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.324	0.594	0.513	0.344	0.178	0.121	0.313	0.168	0.286	0.426	0.380	0.294
N	14785	795	379	15959	14785	795	379	15959	14785	795	379	15959

C.2.5.2. Crisis 2007-2008

Table C.44.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Crisis Defined as 2007-2008.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.00257	-0.0620**	-0.0298	-0.00714
	(-0.28)	(-2.01)	(-0.88)	(-0.84)
δ_c	-0.00415***	0.00397	-0.00162	-0.00406***
	(-5.95)	(1.39)	(-0.36)	(-6.13)
$CREDRSK$	0.771***	0.894***	0.845***	0.779***
	(29.54)	(11.50)	(7.64)	(31.34)
$ZIND$	0.000324	-0.00185*	0.00109	0.000132
	(1.22)	(-1.78)	(0.58)	(0.51)
$SDROA$	-0.00685***	-0.0159***	-0.0140*	-0.00844***
	(-3.61)	(-2.76)	(-1.94)	(-4.84)
$BKSIZE$	-0.0224***	-0.0569**	-0.0184	-0.0244***
	(-3.19)	(-2.47)	(-0.83)	(-4.11)
$BKHHI$	-0.0115*	-0.0941***	-0.145***	-0.0160***
	(-1.90)	(-4.24)	(-2.77)	(-2.72)
$BKMSML$	0.0162***	0.107***	0.121*	0.0169***
	(4.87)	(4.64)	(1.83)	(5.28)
$BKPOP$	0.00161	0.00118	-0.0268	0.00164
	(0.96)	(0.20)	(-1.32)	(1.01)
$BKPDNS$	-0.0102***	0.00695	0.00843	-0.0108***
	(-3.06)	(0.52)	(0.30)	(-3.33)
$BKICHG$	0.0907***	0.142**	0.0356	0.0933***

Continued on next page

Table C.44 – *Continued from previous page*

	Small	Medium	Large	Full
	(9.81)	(2.05)	(0.32)	(10.30)
$MBHC$	0.00667	0.0408***	0.0500**	0.00786
	(1.00)	(2.61)	(2.32)	(1.25)
$OBHC$	0.000894	0.0337**	0.0397***	0.00320
	(0.16)	(2.27)	(2.77)	(0.58)
MRG	0	0.0612***	0	0.0551***
	(.)	(3.53)	(.)	(8.76)
ACQ	0.00294	-0.0201	-0.00961	0.00146
	(0.95)	(-1.43)	(-0.41)	(0.48)
Constant	0.0322	0.420	0.348	0.0604
	(0.38)	(1.33)	(0.74)	(0.81)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.453	0.535	0.579	0.460
N	15310	798	436	16544

Table C.45.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Crisis Defined as 2007-2008.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0192***	0.000789	0.00235	-0.0139***	0.00469	0.0141*	0.000853	0.00436	0.0268***	0.0250	0.000752	0.0252***
	(-6.62)	(0.08)	(0.33)	(-5.24)	(1.35)	(1.77)	(0.08)	(1.40)	(2.63)	(1.03)	(0.02)	(2.71)
δ_c	0.00510***	0.00700***	0.00761***	0.00555***	-0.000355	-0.000899	-0.00401	-0.000433	0.000231	0.00113	-0.00165	0.000207
	(20.63)	(5.70)	(5.60)	(23.53)	(-1.07)	(-0.80)	(-1.61)	(-1.39)	(0.28)	(0.37)	(-0.28)	(0.26)
$CREDRSK$	0.0589***	0.0282	0.0487	0.0595***	-0.198***	-0.0401	-0.0305	-0.188***	-0.802***	-0.666***	-0.464**	-0.794***
	(8.43)	(0.80)	(1.36)	(8.90)	(-16.71)	(-1.01)	(-0.70)	(-16.85)	(-25.82)	(-6.32)	(-2.54)	(-26.56)
$ZIND$	-0.000686***	-0.000197	-0.00132	-0.000719***	-0.000328	0.000499	-0.00200*	-0.000375	-0.00141**	0.00291	0.00213	-0.00107*
	(-3.50)	(-0.27)	(-1.36)	(-3.87)	(-1.24)	(0.41)	(-1.95)	(-1.49)	(-2.34)	(1.15)	(0.83)	(-1.86)
$SDROA$	0.0285***	0.0313***	0.0413***	0.0293***	-0.0182***	-0.0207***	-0.00369	-0.0174***	0.0305***	0.00813	-0.0103	0.0273***
	(14.11)	(4.15)	(7.26)	(15.65)	(-9.08)	(-4.64)	(-0.35)	(-9.30)	(6.38)	(0.59)	(-0.55)	(6.26)
$BKSIZE$	0.0290***	0.0257***	-0.0113*	0.0245***	-0.0203***	-0.00477	-0.00357	-0.0171***	0.0154*	-0.00871	0.0195	0.0155**
	(12.25)	(3.02)	(-1.90)	(12.15)	(-6.17)	(-0.78)	(-0.73)	(-6.33)	(1.82)	(-0.63)	(1.27)	(2.25)
$BKHHI$	0.0200***	0.0335	0.136***	0.0246***	-0.00747	0.0163	0.0982**	-0.00337	0.0271	0.0871	0.0282	0.0299*
	(3.62)	(0.62)	(4.51)	(4.41)	(-1.12)	(0.74)	(2.51)	(-0.51)	(1.51)	(1.38)	(0.23)	(1.73)
$BKMSML$	-0.0355***	-0.0569***	-0.119**	-0.0370***	0.00604*	0.00312	0.00877	0.00820**	-0.00339	-0.0214	-0.152	-0.00629
	(-11.22)	(-3.16)	(-2.12)	(-11.96)	(1.70)	(0.21)	(0.37)	(2.42)	(-0.35)	(-0.55)	(-1.56)	(-0.69)
$BKPOP$	0.00439***	0.00963	0.0242***	0.00540***	-0.00211	0.00143	0.0111	-0.00183	-0.00586	0.000856	0.0636**	-0.00499
	(3.87)	(1.61)	(2.70)	(4.90)	(-1.23)	(0.38)	(1.42)	(-1.15)	(-1.46)	(0.07)	(2.36)	(-1.33)
$BKPDNS$	0.00863***	0.0350***	0.00330	0.0104***	-0.00342	-0.00659	-0.000636	-0.00321	0.00597	-0.0156	-0.0789	0.00568
	(3.77)	(2.72)	(0.17)	(4.58)	(-1.15)	(-1.05)	(-0.04)	(-1.16)	(0.69)	(-0.78)	(-1.29)	(0.70)
$BKICHG$	-0.0641***	-0.222**	0.228*	-0.0700***	-0.0519***	-0.0558	-0.392***	-0.0562***	0.111***	-0.291	-0.641*	0.104***
	(-8.52)	(-2.59)	(1.68)	(-9.39)	(-4.96)	(-0.99)	(-3.10)	(-5.44)	(4.51)	(-1.60)	(-1.93)	(4.31)
$MBHC$	0.00652***	-0.00846	-0.00133	0.00587***	-0.0130***	-0.000867	-0.109***	-0.0149***	-0.00572	0.000502	-0.0262	-0.00727
	(2.96)	(-1.25)	(-0.11)	(2.76)	(-3.35)	(-0.20)	(-17.42)	(-3.88)	(-0.67)	(0.02)	(-0.76)	(-0.92)
$OBHC$	0.00488**	-0.00416	0.00202	0.00485***	-0.00780**	-0.00216	-0.110***	-0.0105***	-0.0161**	-0.0143	-0.0286	-0.0170**

Continued on next page

Table C.45 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(2.51)	(-0.66)	(0.19)	(2.59)	(-2.22)	(-0.55)	(-22.20)	(-2.93)	(-2.22)	(-0.58)	(-0.89)	(-2.44)
MRG	0	-0.0146**	0	-0.0108***	0	0.0142***	0	0.0268***	0	-0.0288**	0	-0.0395***
	(.)	(-2.20)	(.)	(-6.07)	(.)	(3.95)	(.)	(10.94)	(.)	(-2.02)	(.)	(-6.67)
ACQ	-0.00216**	0.00382	0.00403	-0.00193*	0.0000621	0.000231	0.00236	0.000616	0.00267	-0.00766	0.0129	0.00308
	(-1.99)	(0.63)	(1.26)	(-1.86)	(0.04)	(0.07)	(0.57)	(0.46)	(0.77)	(-0.32)	(0.49)	(0.90)
Constant	-0.433***	-0.566***	-0.171	-0.404***	0.569***	0.209***	0.129	0.523***	0.753***	0.968***	-0.120	0.737***
	(-14.76)	(-5.13)	(-1.44)	(-15.50)	(13.96)	(2.79)	(1.19)	(15.00)	(7.42)	(4.27)	(-0.28)	(8.50)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.247	0.457	0.488	0.258	0.154	0.0953	0.343	0.146	0.222	0.202	0.143	0.219
N	15310	798	436	16544	15310	798	436	16544	15310	798	436	16544

C.2.6. Impact of Pre-2006 Managerial Ability

Table C.46.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Managerial Ability Measured in 2005.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2005 interacted with a dummy for whether the observation is in the financial crisis ($MA_{05} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{05} \times \delta_c$	-0.0208*	0.0317	-0.139	-0.0223**
	(-1.91)	(0.68)	(-1.56)	(-2.07)
δ_c	-0.0156***	-0.00770	-0.0184**	-0.0165***
	(-14.07)	(-1.05)	(-2.13)	(-14.94)
$CREDRSK$	0.741***	0.639***	0.889***	0.747***
	(33.01)	(7.05)	(6.42)	(34.64)
$ZIND$	0.000173	0.00109	0.00805	0.000313
	(0.31)	(0.48)	(1.62)	(0.58)
$SDROA$	-0.0184***	-0.0347***	-0.0388***	-0.0208***
	(-5.44)	(-3.61)	(-2.72)	(-6.64)
$BKSIZE$	-0.0473***	-0.0622**	0.00184	-0.0422***
	(-8.89)	(-2.20)	(0.11)	(-8.97)
$BKHHI$	-0.00274	-0.114	-0.494***	-0.0165
	(-0.22)	(-1.63)	(-3.96)	(-1.30)
$BKMSML$	0.0390***	0.0377	0.0945	0.0395***
	(5.73)	(0.95)	(1.04)	(6.00)
$BKPOP$	0.00228	0.0153	-0.0361	0.00210
	(0.74)	(1.39)	(-1.22)	(0.71)
$BKPDNS$	-0.0147**	-0.0106	0.0803	-0.0151**
	(-2.38)	(-0.48)	(1.07)	(-2.53)

Continued on next page

Table C.46 – *Continued from previous page*

	Small	Medium	Large	Full
$BKICHG$	0.225***	0.598***	0.230	0.260***
	(9.83)	(5.02)	(0.84)	(11.60)
$MBHC$	0.0138*	0.0426**	-0.00184	0.0130*
	(1.76)	(2.14)	(-0.04)	(1.74)
$OBHC$	0.0126*	0.0587***	-0.00326	0.0133**
	(1.90)	(3.80)	(-0.09)	(2.07)
MRG	0	0.0830***	0	0.0710***
	(.)	(4.39)	(.)	(14.55)
ACQ	0.00326	-0.0213	-0.0144	0.00191
	(0.86)	(-1.64)	(-0.44)	(0.52)
Constant	0.335***	0.570	0.0387	0.291***
	(4.80)	(1.63)	(0.10)	(4.53)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.228	0.277	0.365	0.232
N	19819	1049	516	21384

Table C.47.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Managerial Ability Measured in 2005.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2005 interacted with a dummy for whether the observation is in the financial crisis ($MA_{05} \times \delta_c$), a crisis dummy (δ_c)and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{05} \times \delta_c$	-0.0215***	-0.000723	-0.0123	-0.0185***	0.000284	0.00672	0.0172	0.00103	0.0513***	0.0548**	0.0265	0.0509***
	(-8.12)	(-0.07)	(-1.00)	(-7.41)	(0.08)	(0.84)	(1.26)	(0.32)	(5.18)	(2.30)	(0.59)	(5.53)
δ_c	0.00565***	0.00868***	0.0132***	0.00606***	0.00139***	-0.000409	-0.00219	0.00126***	0.00146	-0.00822	-0.00575	0.000880
	(18.77)	(4.72)	(4.40)	(20.49)	(3.11)	(-0.24)	(-0.59)	(2.96)	(1.30)	(-1.43)	(-0.54)	(0.80)
$CREDRSK$	0.0485***	0.0452*	-0.0168	0.0486***	-0.198***	-0.0510	-0.0597	-0.189***	-0.806***	-0.590***	-0.517***	-0.794***
	(8.93)	(1.77)	(-0.46)	(9.26)	(-20.89)	(-1.27)	(-1.44)	(-21.20)	(-31.78)	(-8.60)	(-3.14)	(-33.19)
$ZIND$	-0.000444***	0.000344	-0.00106	-0.000493***	0.0000557	0.00137	-0.00213**	0.0000403	0.000235	0.000595	-0.000903	0.000269
	(-2.68)	(0.56)	(-0.90)	(-3.12)	(0.22)	(1.56)	(-2.03)	(0.17)	(0.38)	(0.30)	(-0.33)	(0.46)
$SDROA$	0.0214***	0.0274***	0.0473***	0.0232***	-0.0133***	-0.0143***	-0.000774	-0.0124***	0.0199***	0.00480	-0.00745	0.0182***
	(12.72)	(3.92)	(6.97)	(14.44)	(-7.03)	(-3.04)	(-0.08)	(-7.06)	(4.63)	(0.36)	(-0.37)	(4.51)
$BKSIZE$	0.0206***	0.0236***	-0.0115**	0.0194***	-0.0178***	0.00359	-0.0108*	-0.0146***	0.0156***	0.0135	0.0218	0.0135***
	(11.87)	(2.86)	(-2.28)	(12.97)	(-7.22)	(0.69)	(-1.68)	(-7.39)	(2.70)	(1.08)	(1.07)	(2.78)
$BKHHI$	0.0203***	0.0127	0.133***	0.0233***	-0.000580	-0.0151	0.0634	0.00233	0.0229	0.00714	-0.0886	0.0221
	(4.02)	(0.27)	(4.09)	(4.58)	(-0.09)	(-0.62)	(1.14)	(0.36)	(1.36)	(0.09)	(-0.64)	(1.36)
$BKMSML$	-0.0253***	-0.0479***	-0.0884**	-0.0259***	0.00520	0.00324	-0.0205	0.00723**	-0.0141	-0.00614	-0.134*	-0.0183**
	(-9.16)	(-3.82)	(-2.28)	(-9.43)	(1.44)	(0.27)	(-0.87)	(2.13)	(-1.58)	(-0.14)	(-1.75)	(-2.16)
$BKPOP$	0.00353***	0.00628	0.00751	0.00360***	-0.00238	0.000160	0.0156**	-0.00228	-0.000454	0.0146	0.0730***	0.000421
	(3.60)	(1.24)	(1.12)	(3.83)	(-1.58)	(0.04)	(2.05)	(-1.61)	(-0.14)	(1.13)	(3.24)	(0.14)
$BKPDNS$	0.00716***	0.0209**	0.0211	0.00853***	0.00102	-0.00263	-0.00535	0.00175	-0.000380	-0.0230	-0.135**	-0.000293
	(3.29)	(2.16)	(1.10)	(4.08)	(0.36)	(-0.42)	(-0.34)	(0.69)	(-0.04)	(-1.09)	(-2.43)	(-0.04)
$BKICHG$	-0.0394***	-0.173**	0.0770	-0.0424***	-0.0516***	-0.0185	-0.255	-0.0559***	0.0777***	-0.225	-0.507	0.0711**
	(-4.62)	(-2.19)	(0.61)	(-4.98)	(-4.32)	(-0.37)	(-1.59)	(-4.72)	(2.67)	(-1.11)	(-1.18)	(2.48)
$MBHC$	0.00317	-0.00755	0.0159**	0.00267	-0.0121***	-0.00880	-0.135***	-0.0133***	-0.0194**	-0.00193	-0.0852**	-0.0181**
	(1.51)	(-1.50)	(2.00)	(1.33)	(-3.37)	(-1.63)	(-21.09)	(-3.84)	(-2.27)	(-0.14)	(-2.53)	(-2.25)
$OBHC$	0.00212	-0.00539	0.0201***	0.00198	-0.00650**	-0.00821*	-0.133***	-0.00841***	-0.0260***	-0.0235***	-0.0933***	-0.0255***

Continued on next page

Table C.47 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(1.13)	(-1.34)	(4.38)	(1.09)	(-2.05)	(-1.73)	(-34.50)	(-2.67)	(-3.47)	(-2.69)	(-3.00)	(-3.56)
MRG	0	-0.0205***	0	-0.00486***	0	0.00949**	0	0.0255***	0	-0.0686***	0	-0.0553***
	(.)	(-3.32)	(.)	(-3.39)	(.)	(2.36)	(.)	(12.72)	(.)	(-4.17)	(.)	(-11.44)
ACQ	-0.000765	0.00115	0.00508	-0.000603	-0.00117	-0.00212	0.00348	-0.000913	0.00143	0.00910	-0.00177	0.00198
	(-0.84)	(0.25)	(1.39)	(-0.69)	(-0.77)	(-1.18)	(1.26)	(-0.64)	(0.39)	(0.86)	(-0.06)	(0.56)
Constant	-0.317***	-0.463***	0.0345	-0.312***	0.525***	0.113	0.257*	0.481***	0.723***	0.432*	-0.00514	0.729***
	(-14.07)	(-4.54)	(0.31)	(-15.26)	(16.48)	(1.55)	(1.92)	(17.52)	(9.39)	(1.88)	(-0.01)	(10.77)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.233	0.425	0.540	0.250	0.173	0.0690	0.312	0.165	0.291	0.333	0.273	0.291
N	15368	791	424	16583	15368	791	424	16583	15368	791	424	16583

C.2.7. Using Lagged Regressors

Table C.48.: Bank Liquidity Creation and Managerial Ability, Lagged Regressors.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are lagged three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
MA_{t-1}	0.0479***	0.0791***	-0.00425	0.0429***
	(6.18)	(2.92)	(-0.10)	(5.47)
$CREDRSK_{t-1}$	0.314***	0.184***	0.252***	0.312***
	(34.99)	(4.40)	(3.33)	(35.40)
$ZIND_{t-1}$	-0.000871**	-0.00221	0.000452	-0.000635*
	(-2.30)	(-1.43)	(0.13)	(-1.73)
$SDROA_{t-1}$	0.000200	-0.0307**	-0.0335	-0.00120
	(0.07)	(-2.26)	(-1.37)	(-0.41)
$BKSIZE_{t-1}$	-0.0132***	-0.00902	0.0150	-0.0133***
	(-4.75)	(-0.94)	(1.12)	(-5.34)
$BKHHI_{t-1}$	0.0351***	0.0578	0.0829	0.0323***
	(3.48)	(0.76)	(0.38)	(3.15)
$BKMSML_{t-1}$	0.0135**	-0.0221	-0.144**	0.0129**
	(2.48)	(-0.83)	(-2.23)	(2.45)
$BKPOP_{t-1}$	0.00945***	0.0311***	0.0169	0.00982***
	(4.77)	(3.88)	(0.89)	(5.20)
$BKPDNS_{t-1}$	0.00222	-0.0151	0.0131	-0.000826
	(0.51)	(-0.95)	(0.39)	(-0.20)
$BKICHG_{t-1}$	0.167***	0.410**	0.368	0.178***
	(8.34)	(2.56)	(0.86)	(8.93)
$MBHC_{t-1}$	0.0234***	0.00381	0.000262	0.0234***
	(5.83)	(0.26)	(0.01)	(6.10)
$OBHC_{t-1}$	0.0206***	0.00584	0.00653	0.0210***

Continued on next page

Table C.48 – *Continued from previous page*

	Small	Medium	Large	Full
	(6.60)	(0.44)	(0.19)	(6.86)
MRG_{t-1}	0.0358**	0.111**	0.0721***	0.0827***
	(2.07)	(2.19)	(3.40)	(3.75)
ACQ_{t-1}	-0.00201	-0.00276	0.00680	-0.00195
	(-1.11)	(-0.35)	(0.45)	(-1.11)
Constant	0.0793**	-0.0206	-0.128	0.0927***
	(2.17)	(-0.12)	(-0.41)	(2.75)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.350	0.306	0.162	0.344
N	77267	3312	1844	82423

Table C.49.: Bank Risk-Taking and Managerial Ability, Lagged Regressors.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on lagged managerial ability (MA_{t-1}) and controls with bank and time fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are lagged three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
MA_{t-1}	-0.000911	-0.0123***	-0.00311	-0.00146	-0.00845***	0.0166	0.00811	-0.00316	-0.0673***	-0.0379	0.0257	-0.0547***
	(-0.81)	(-3.12)	(-0.54)	(-1.35)	(-3.08)	(1.53)	(1.18)	(-1.23)	(-10.59)	(-1.60)	(0.76)	(-8.77)
$CREDRSK$	0.0201***	0.0153**	0.0264***	0.0199***	-0.212***	-0.0900***	-0.0861***	-0.205***	-0.649***	-0.617***	-0.633***	-0.652***
	(15.84)	(2.29)	(3.05)	(16.23)	(-47.50)	(-6.50)	(-5.18)	(-47.72)	(-58.18)	(-13.04)	(-11.50)	(-60.87)
$ZIND$	-0.000440***	-0.0000494	-0.000422	-0.000409***	0.000632***	0.000256	0.0000544	0.000572***	0.000399	0.00206	0.00148	0.000279
	(-7.83)	(-0.23)	(-0.94)	(-7.44)	(3.69)	(0.48)	(0.08)	(3.50)	(1.19)	(1.64)	(0.90)	(0.87)
$SDROA$	0.0124***	0.0162***	0.0221***	0.0129***	-0.00786***	0.00145	0.00307	-0.00614***	0.00797***	0.0186***	0.000500	0.00916***
	(20.12)	(7.72)	(6.19)	(22.30)	(-7.47)	(0.37)	(0.77)	(-6.16)	(3.78)	(2.87)	(0.03)	(4.64)
$BKSIZE$	0.00490***	0.00526***	0.00171	0.00459***	-0.00466***	-0.00193	-0.00810***	-0.00250**	0.00510**	-0.00254	0.0180*	0.00803***
	(10.82)	(3.12)	(0.89)	(11.78)	(-3.70)	(-0.36)	(-2.73)	(-2.35)	(2.27)	(-0.29)	(1.70)	(4.06)
$BKHHI$	-0.00203	-0.00774	0.00139	-0.00212	-0.00354	-0.0190	0.0347	-0.00166	0.00600	-0.0545	-0.0757	0.0101
	(-1.25)	(-0.70)	(0.13)	(-1.34)	(-0.85)	(-0.69)	(0.90)	(-0.40)	(0.75)	(-1.11)	(-0.58)	(1.27)
$BKMSML$	-0.00593***	0.00196	-0.00757	-0.00551***	-0.000869	0.0191	0.0161	0.000853	-0.0153***	0.0200	0.0398	-0.0112***
	(-6.68)	(0.46)	(-0.90)	(-6.41)	(-0.38)	(1.45)	(1.56)	(0.40)	(-3.50)	(0.90)	(0.89)	(-2.67)
$BKPOP$	0.000903***	-0.000647	-0.00208	0.000833***	0.000279	-0.00274	0.000139	-0.0000727	-0.00472***	-0.00282	0.00683	-0.00450***
	(3.19)	(-0.43)	(-1.48)	(3.03)	(0.38)	(-0.74)	(0.06)	(-0.11)	(-3.11)	(-0.37)	(0.53)	(-3.09)
$BKPDNS$	0.00168***	0.00221	-0.00511*	0.00131**	0.000625	0.0179**	0.00452	0.00213	-0.0000131	0.00326	0.0165	0.00222
	(2.78)	(0.83)	(-1.79)	(2.28)	(0.31)	(2.18)	(0.72)	(1.15)	(-0.00)	(0.27)	(0.55)	(0.67)
$BKICHG$	-0.0849***	-0.128***	-0.0422	-0.0889***	-0.0631***	-0.0973	-0.0318	-0.0699***	0.0202	-0.158	-0.204	0.0100
	(-21.97)	(-4.43)	(-1.07)	(-23.59)	(-7.54)	(-1.43)	(-0.41)	(-8.44)	(1.17)	(-1.43)	(-0.82)	(0.59)
$MBHC$	0.000558	0.0000338	-0.00150	0.000464	-0.0176***	-0.00586	-0.0363**	-0.0177***	-0.00970***	-0.00573	-0.0362	-0.0115***
	(1.02)	(0.01)	(-0.47)	(0.89)	(-9.15)	(-0.89)	(-2.17)	(-9.77)	(-2.86)	(-0.35)	(-1.19)	(-3.55)
$OBHC$	-0.000166	0.000171	-0.00155	-0.000189	-0.0123***	-0.00731	-0.0358**	-0.0132***	-0.0142***	-0.0110	-0.0397	-0.0159***
	(-0.36)	(0.06)	(-0.58)	(-0.42)	(-7.66)	(-1.15)	(-2.11)	(-8.48)	(-5.17)	(-0.69)	(-1.36)	(-5.91)
MRG	0.000750	-0.0118***	-0.000896	0.00172***	0.0257***	-0.000934	-0.00375	0.0134	0.0310	-0.0261*	-0.0226*	-0.0163
	(1.05)	(-4.03)	(-0.67)	(3.72)	(7.95)	(-0.16)	(-1.44)	(1.64)	(0.78)	(-1.89)	(-1.88)	(-0.76)

Continued on next page

Table C.49 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
ACQ	-0.000306	0.000967	0.000271	-0.000238	0.000449	-0.00186	-0.00112	0.000309	0.000940	-0.0155**	0.00449	0.000970
	(-1.25)	(0.87)	(0.18)	(-1.02)	(0.62)	(-0.78)	(-0.40)	(0.45)	(0.65)	(-2.27)	(0.50)	(0.69)
Constant	-0.0577***	-0.0539*	0.0228	-0.0526***	0.360***	0.200***	0.275***	0.329***	0.818***	0.874***	0.240	0.776***
	(-10.05)	(-1.84)	(0.69)	(-10.12)	(23.84)	(2.66)	(5.20)	(24.99)	(28.00)	(4.70)	(1.12)	(28.76)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.312	0.491	0.516	0.325	0.235	0.132	0.181	0.224	0.365	0.357	0.281	0.362
N	79152	3341	1863	84356	79152	3341	1863	84356	79152	3341	1863	84356

Table C.50.:
Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis, Lagged Regressors.

This table reports results from fixed effects regressions of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c) and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0138	-0.0460	-0.0697*	-0.0184
	(-1.06)	(-0.92)	(-1.67)	(-1.52)
δ_c	0.00227**	0.00168	0.000410	0.00231**
	(2.26)	(0.28)	(0.04)	(2.35)
$CREDRSK_{t-1}$	0.0465*	-0.279**	-0.140	0.0238
	(1.89)	(-2.43)	(-0.85)	(1.00)
$ZIND_{t-1}$	0.000275	0.00477	0.00700	0.000696
	(0.40)	(1.47)	(1.41)	(1.04)
$SDROA_{t-1}$	-0.0135**	-0.0363*	-0.0595	-0.0162***
	(-2.54)	(-1.77)	(-1.47)	(-3.19)
$BKSIZE_{t-1}$	-0.0605***	-0.0650***	-0.0789**	-0.0633***
	(-8.72)	(-2.81)	(-2.59)	(-10.02)
$BKHHI_{t-1}$	0.00379	0.00469	-0.563***	-0.0115
	(0.18)	(0.04)	(-2.87)	(-0.55)
$BKMSML_{t-1}$	0.0523***	0.0621	0.0411	0.0509***
	(4.69)	(1.22)	(0.35)	(4.73)
$BKPOP_{t-1}$	0.00175	0.0104	-0.0443	0.00238
	(0.41)	(0.63)	(-1.33)	(0.58)
$BKPDNS_{t-1}$	-0.0357***	-0.0707**	0.0351	-0.0389***
	(-3.16)	(-2.43)	(0.50)	(-3.59)
$BKICHG_{t-1}$	0.0431*	0.576**	0.528	0.0587**
	(1.68)	(2.14)	(1.15)	(2.28)
$MBHC_{t-1}$	-0.0113	-0.00801	-0.0129	-0.0112
	(-1.35)	(-0.33)	(-0.26)	(-1.40)
$OBHC_{t-1}$	-0.00282	0.0214	0.00473	-0.000431
	(-0.40)	(1.04)	(0.10)	(-0.06)
MRG_{t-1}	0	0.0706***	0	0.0603***
	(.)	(4.28)	(.)	(9.92)
ACQ_{t-1}	0.00703*	-0.0273**	-0.00934	0.00546
	(1.74)	(-2.03)	(-0.21)	(1.39)
Constant	1.042***	1.561***	2.358***	1.116***
	(11.91)	(5.86)	(4.63)	(13.82)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.0256	0.108	0.101	0.0297
N	18652	1029	497	20178

Table C.51.: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis, Lagged Regressors.

This table reports results from fixed effects regressions of three measures of bank risk, nonperforming loans over total loans (NPL), tier 1 ratio ($T1R$) and liquid assets over total assets ($LAGTA$) on managerial ability as of December 2006 interacted with a dummy for whether the observation is in the financial crisis ($MA_{06} \times \delta_c$), a crisis dummy (δ_c)and controls with bank fixed effects and standard errors clustered by bank. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels. T-statistics are reported in brackets. Controls are lagged three year moving averages and include the log of gross total assets ($BKSIZE$). The sum of risk weighted assets scaled by gross total assets ($CREDRSK$), the standard deviation of return on assets ($SDROA$) and the Z-Score ($ZIND$) capture risk. The last two variables are orthogonalized against $CREDRSK$. The regressions also include bank demographic factors. These are $BKHHI$, $BKPOP$, $BKPDNS$, $BKICHG$ and $BKMSML$ and are calculated by weighting the demographic variables HHI (Herfindahl index), population, population density, income growth and market share of medium and large banks by the share of deposits each MSA or non-MSA county represents of a bank's total deposits. $MBHC$ ($OBHC$) are dummy variables set to 1 if the bank belongs to a multibank (onebank) holding company. MRG (ACQ) are dummy variables set to 1 if the bank was involved in mergers (acquisitions) within the last three years. MA represents managerial ability as obtained following the methodology of Demerjian, Lev and McVay (2012), using DEA profit efficiency and standard first stage regressors on yearly subsamples. Monetary values are in 2005 US Dollars.

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
$MA_{06} \times \delta_c$	-0.0279***	-0.0137	0.00911	-0.0238***	0.0119***	0.0193**	-0.00570	0.0113***	0.0584***	0.0330	0.0437	0.0534***
	(-8.17)	(-1.30)	(0.97)	(-7.48)	(3.12)	(2.09)	(-0.55)	(3.29)	(5.12)	(1.19)	(1.47)	(5.23)
δ_c	0.00677***	0.0128***	0.0134***	0.00722***	-0.00280***	-0.00180	0.000932	-0.00267***	-0.000555	0.00285	-0.000561	-0.000432
	(24.73)	(8.98)	(7.67)	(27.10)	(-8.02)	(-1.61)	(0.37)	(-8.02)	(-0.65)	(0.79)	(-0.08)	(-0.53)
$CREDRSK_{t-1}$	0.0397***	0.0246	0.0573**	0.0402***	-0.0815***	-0.00302	-0.0559**	-0.0779***	-0.284***	-0.229***	-0.241**	-0.284***
	(9.99)	(1.19)	(2.16)	(10.38)	(-13.93)	(-0.16)	(-2.36)	(-14.05)	(-19.15)	(-3.87)	(-2.28)	(-19.82)
$ZIND_{t-1}$	-0.0000811	0.000630	0.000410	0.00000521	-0.0000331	-0.000123	-0.000280	-0.0000317	0.000325	0.00264**	0.00188	0.000688**
	(-0.97)	(1.59)	(0.53)	(0.06)	(-0.28)	(-0.38)	(-0.50)	(-0.29)	(1.13)	(1.98)	(0.82)	(2.46)
$SDROA_{t-1}$	0.00387***	0.00430	0.0130**	0.00422***	-0.00630***	-0.00272	-0.00701*	-0.00591***	0.00568**	0.00386	0.0110	0.00578***
	(4.58)	(1.62)	(2.01)	(5.17)	(-6.83)	(-1.24)	(-1.77)	(-6.90)	(2.53)	(0.61)	(0.78)	(2.77)
$BKSIZE_{t-1}$	0.0242***	0.0228***	0.000109	0.0240***	-0.0119***	0.00776***	-0.00773	-0.00841***	-0.00679	0.0169*	0.0340	0.000590
	(11.79)	(4.83)	(0.02)	(13.55)	(-4.68)	(2.95)	(-1.39)	(-4.04)	(-1.29)	(1.82)	(1.60)	(0.13)
$BKHHI_{t-1}$	0.00322	0.00602	0.0899***	0.00531**	0.00436	0.0201	0.115***	0.00727**	0.0237***	0.111**	0.243***	0.0309***
	(1.31)	(0.49)	(4.95)	(2.17)	(1.53)	(1.59)	(3.23)	(2.50)	(3.01)	(2.55)	(3.13)	(3.92)
$BKMSML_{t-1}$	-0.0152***	-0.0220***	-0.0522*	-0.0157***	-0.00160	-0.0181***	-0.0334	-0.000939	-0.0523***	-0.0467**	-0.0869	-0.0513***
	(-10.84)	(-2.59)	(-1.68)	(-11.44)	(-1.10)	(-2.68)	(-1.33)	(-0.67)	(-12.02)	(-2.15)	(-0.97)	(-12.10)
$BKPOP_{t-1}$	0.00243***	0.00435	0.0208***	0.00273***	0.000227	0.000339	0.00993*	0.000335	0.00170	-0.00286	0.0265*	0.00189
	(4.55)	(1.54)	(3.83)	(5.07)	(0.32)	(0.17)	(1.67)	(0.49)	(0.91)	(-0.46)	(1.67)	(1.04)
$BKPDNS_{t-1}$	0.00428***	0.0245***	-0.0141	0.00566***	-0.000996	0.00870	0.00124	-0.0000544	0.0113***	0.0358**	-0.0269	0.0136***
	(3.47)	(3.15)	(-1.59)	(4.46)	(-0.69)	(1.22)	(0.13)	(-0.04)	(2.75)	(2.34)	(-0.81)	(3.35)
$BKICHG_{t-1}$	-0.0287***	-0.188***	-0.171***	-0.0334***	-0.0118***	-0.00701	-0.0856	-0.0141***	0.0497***	-0.201***	-0.165	0.0413***
	(-9.40)	(-6.31)	(-3.02)	(-10.89)	(-3.20)	(-0.28)	(-1.29)	(-3.84)	(5.12)	(-2.68)	(-0.85)	(4.28)
$MBHC_{t-1}$	0.00413**	-0.0136	-0.00550	0.00390*	-0.00418	-0.0113	-0.0456***	-0.00546**	0.0177***	-0.00253	0.0243	0.0146**
	(1.96)	(-1.60)	(-0.57)	(1.89)	(-1.50)	(-1.61)	(-8.58)	(-2.02)	(2.66)	(-0.12)	(1.06)	(2.30)
$OBHC_{t-1}$	0.00335*	-0.0104	-0.00906	0.00261	-0.00386	-0.00892	-0.0511***	-0.00520**	0.00836	-0.00478	0.0130	0.00681

Continued on next page

Table C.51 – *Continued from previous page*

	Panel A: NPL				*Panel B: T1R*				*Panel C: LAGTA*			
Parameter	Small	Medium	Large	Full	Small	Medium	Large	Full	Small	Medium	Large	Full
	(1.78)	(-1.37)	(-1.23)	(1.43)	(-1.52)	(-1.40)	(-15.02)	(-2.06)	(1.45)	(-0.25)	(0.70)	(1.23)
MRG_{t-1}	0	-0.0471***	0	-0.0221***	0	-0.0113	0	0.0108***	0	-0.0310	0	0.00708
	(.)	(-4.89)	(.)	(-9.70)	(.)	(-1.43)	(.)	(4.17)	(.)	(-1.56)	(.)	(1.07)
ACQ_{t-1}	-0.00204**	0.00344	0.00313	-0.00170*	-0.00213*	0.00175	0.000975	-0.00180	-0.00829**	-0.00306	0.00368	-0.00768**
	(-2.03)	(0.52)	(0.43)	(-1.74)	(-1.73)	(0.33)	(0.37)	(-1.52)	(-2.48)	(-0.27)	(0.22)	(-2.41)
Constant	-0.333***	-0.434***	-0.253**	-0.344***	0.349***	-0.00954	0.176	0.302***	0.556***	0.165	-0.310	0.460***
	(-13.33)	(-5.96)	(-2.16)	(-15.44)	(10.90)	(-0.21)	(1.56)	(11.03)	(8.27)	(1.21)	(-0.80)	(7.75)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.173	0.403	0.296	0.186	0.0746	0.0348	0.177	0.0679	0.0846	0.115	0.126	0.0844
N	18652	1029	497	20178	18652	1029	497	20178	18652	1029	497	20178

Bibliography

Aghion, Philippe, Patrick Bolton and Steven Fries. (1999) "Optimal Design of Bank Bailouts: The Case of Transition Economies." *Journal of Institutional and Theoretical Economics (JITE) / Zeitschrift für die gesamte Staatswissenschaft* 155, 51–70.

Ahmad, Rubi, Mohamed Ariff and Michael Skully. (2007) "Factors Determining Mergers of Banks in Malaysia's Banking Sector Reform." *Multinational Finance Journal* 11, 1–31.

Aigner, Dennis, C. A. Knox Lovell and Peter Schmidt. (1977) "Formulation and Estimation of Stochastic Production Frontier Models." *Journal of Econometrics* 6, 21–37.

Akhigbe, Aigbe and James E. McNulty. (2003) "The Profit Efficiency of Small US Commercial Banks." *Journal of Banking & Finance* 27, 307–325.

Altunbas, Yener and S. P. Chakravarty. (2001) "Frontier cost functions and bank efficiency." *Economics Letters* 72, 233–240.

Altunbas, Yener, Lynne Evans and Philip Molyneux. (2001) "Bank Ownership and Efficiency." *Journal of Money, Credit & Banking* 33, 926–954.

Andreou, Panayiotis C., Ian Cooper, Christodoulos Louca and Dennis Philip. (2013) *Accounting Conservatism and Crash Risk: Evidence from the Banking Industry.* Working paper.

Andreou, Panayiotis C., Daphna Ehrlich and Christodoulos Louca. (2013) *Managerial Ability and Firm Performance: Evidence from the Global Financial Crisis.* Working Paper.

Asaftei, Gabriel. (2008) "The Contribution of Product Mix versus Efficiency and Technical Change in US Banking." *Journal of Banking & Finance* 32, 2336–2345.

Athanassopoulos, Antreas D. and Stephen P. Curram. (1996) "A Comparison of Data Envelopment Analysis and Artificial Neural Networks as Tools for Assessing the Efficiency of Decision Making Units." *The Journal of the Operational Research Society* 47, 1000–1016.

Azadeh, A., S. F. Ghaderi, M. Anvari, M. Saberi and H. Izadbakhsh. (2007) "An integrated artificial neural network and fuzzy clustering algorithm for performance assessment of decision making units." *Applied Mathematics and Computation* 187, 584–599.

Azadeh, A., M. Saberi and M. Anvari. (2011) "An Integrated Artificial Neural Network Fuzzy C-Means-Normalization Algorithm for performance assessment of decision-making units: The cases of auto industry and power plant." *Computers & Industrial Engineering* 60, 328–340.

Azadeh, Ali, Morteza Saberi and Mona Anvari. (2010) "An integrated artificial neural network algorithm for performance assessment and optimization of decision making units." *Expert Systems with Applications* 37, 5688–5697.

Balboa, Marina, Germán López-Espinosa and Antonio Rubia. (2013) "Nonlinear dynamics in discretionary accruals: An analysis of bank loan-loss provisions." *Journal of Banking & Finance* 37, 5186–5207.

Bamber, Linda Smith, John Jiang and Isabel Yanyan Wang. (2010) "What's My Style? The Influence of Top Managers on Voluntary Corporate Financial Disclosure." *Accounting Review* 85, 1131–1162.

Barr, Richard S., Lawrence M. Seiford and Thomas F. Siems. (1993) "An envelopment-analysis approach to measuring the managerial efficiency of banks." *Annals of Operations Research* 45, 1–19.

Barr, Richard S. and Thomas F. Siems. (1997) "Bank Failure Prediction Using Dea to Measure Management Quality." Operations Research/Computer Science Interfaces Series vol. 7. In *Interfaces in Computer Science and Operations Research,* edited by Barr, Richard S., Richard V. Helgason and Jeffery L. Kennington, pp. 341–365. Norwell, MA: Kluwer Academic Publishers.

Battese, G. E. and T. J. Coelli. (1992) "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India." *Journal of Productivity Analysis* 3, 153–169.

Battese, G. E. and T. J. Coelli. (1995) "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* 20, 325–332.

Battese, George E. and Tim J. Coelli. (1988) "Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data." *Journal of Econometrics* 38, 387–399.

Bauer, Paul W., Allen N. Berger, D. Ferrier and David B. Humphrey. (1998) "Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods." *Journal of Economics and Business* 50, 85–114.

Beatty, Anne and Scott Liao. (2011) "Do delays in expected loss recognition affect banks' willingness to lend?" *Journal of Accounting & Economics* 52, 1–20.

Bebchuk, Lucian A. and Itay Goldstein. (2011) "Self-fulfilling Credit Market Freezes." *Review of Financial Studies* 24, 3519–3555.

Bengio, Yoshua, Réjean Ducharme, Pascal Vincent and Christian Jauvin. (2003) "A Neural Probabilistic Language Model." *Journal of Machine Learning Research* 3, 1137–1155.

Bengio, Yoshua and Paolo Frasconi. (1994) "Credit assignment through time: Alternatives to backpropagation." In *Advances in Neural Information Processing Systems,* edited by Tesauro, J. D. Cowan G. and J. Alspector, pp. 75–82. San Matteo, CA: Morgan Kaufman.

Bennedsen, Morten, Francisco Pérez-González and Daniel Wolfenzon. (2006) *Do CEOs Matter?* Working paper.

Berger, Allen N. (1995) "The Profit-Structure Relationship in Banking–Tests of Market-Power and Efficient-Structure Hypotheses." *Journal of Money, Credit & Banking* 27, 404–431.

Berger, Allen N. (2003) "The Economic Effects of Technological Progress: Evidence from the Banking Industry." *Journal of Money, Credit & Banking* 35, 141–176.

Berger, Allen N. and Emilia Bonaccorsi di Patti. (2006) "Capital structure and firm performance: A new approach to testing agency theory and an application to the banking industry." *Journal of Banking & Finance* 30, 1065–1102.

Berger, Allen N., Seth D. Bonime, Lawrence G. Goldberg and Lawrence J. White. (2004) "The Dynamics of Market Entry: The Effects of Mergers and Acquisitions on Entry in the Banking Industry." *Journal of Business* 77, 797–834.

Berger, Allen N. and Christa H. S. Bouwman. (2008) *Financial Crises and Bank Liquidity Creation.* Working paper, Wharton Financial Institutions Research Center.

Berger, Allen N. and Christa H. S. Bouwman. (2009) "Bank Liquidity Creation." *Review of Financial Studies* 22, 3779–3837.

Berger, Allen N. and Christa H. S. Bouwman. (2012) *Bank Liquidity Creation, Monetary Policy, and Financial Crises.* Working paper, Wharton Financial Institutions Center.

Berger, Allen N. and Robert DeYoung. (1997) "Problem Loans and Cost Efficiency in Commercial Banks." *Journal of Banking & Finance* 21, 849–870.

Berger, Allen N. and David B. Humphrey. (1992) "Measurement and Efficiency Issues in Commercial Banking." In *Output measurement in the service sectors,* edited by Griliches, Zvi, pp. 245–279. Chicago and London: University of Chicago Press.

Berger, Allen N. and David B. Humphrey. (1997) "Efficiency of financial institutions: International survey and directions for future research." *European Journal of Operational Research* 98, 175–212.

Berger, Allen N. and Loretta J. Mester. (2003) "Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition." *Journal of Financial Intermediation* 12, 57–95.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan and Jeremy C. Stein. (2005) "Does function follow organizational form? Evidence from the lending practices of large and small banks." *Journal of Financial Economics* 76, 237–269.

Berglöf, Erik and Gérard Roland. (1997) "Soft budget constraints and credit crunches in financial transition." *European Economic Review* 41, 807–817.

Berk, Jonathan B. and Richard Stanton. (2007) "Managerial Ability, Compensation, and the Closed-End Fund Discount." *Journal of Finance* 62, 529–556.

Bertrand, Marianne and Antoinette Schoar. (2003) "Managing with Style: The Effect of Managers on Firm Policies." *Quarterly Journal of Economics* 118, 1169–1208.

Brunnermeier, Markus K. (2009) "Deciphering the Liquidity and Credit Crunch 2007–2008." *Journal of Economic Perspectives* 23, 77–100.

Cantrell, Brett. (2013) *Bank Managerial Ability And Accounting: Do Better Managers Report Higher Quality Loan Loss Reserves and Fair Values?* Working paper, Arizona State University.

Carpenter, Mason A. and James W. Fredrickson. (2001) "Top Management Teams, Global Strategic Posture, and the Moderating Role of Uncertainty." *The Academy of Management Journal* 44, 533–545.

Casu, Barbara and Claudia Girardone. (2006) "Bank Competition, Concentration and Efficiency in the Single European Market." *Manchester School* 74, 441–468.

Casu, Barbara and Claudia Girardone. (2009) "Testing the relationship between competition and efficiency in banking: A panel data analysis." *Economics Letters* 105, 134–137.

Chortareas, Georgios E., Claudia Girardone and Alexia Ventouri. (2011) "Financial Frictions, Bank Efficiency and Risk: Evidence from the Eurozone." *Journal of Business Finance & Accounting* 38, 259–287.

Christoffersen, Peter F. and Francis X. Diebold. (1996) "Further Results on Forecasting and Model Selection Under Asymmetric Loss." *Journal of Applied Econometrics* 11, 561–571.

Christoffersen, Peter F. and Francis X. Diebold. (1997) "Optimal Prediction under Asymmetric Loss." *Econometric Theory* 13, 808–817.

Cipollini, Andrea and Franco Fiordelisi. (2012) "Economic value, competition and financial distress in the European banking system." *Journal of Banking & Finance* 36.

Coelli, T. J. (1996) *A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation.* Working paper, University of New England.

Coelli, Timothy J., D. S. Prasada Rao, Christopher J. O'Donnell and G. E. Battese. (2005) *An Introduction to Efficiency and Productivity Analysis.* 2nd edition. New York: Springer.

Cooper, Ian A. and Sergei A. Davydenko. (2007) "Estimating the Cost of Risky Debt." *Journal of Applied Corporate Finance* 19, 90–95.

Costa, Álvaro and Raphael N. Markellos. (1997) "Evaluating public transport efficiency with neural network models." *Transportation Research Part C: Emerging Technologies* 5, 301–312.

Coval, Joshua D. and Anjan V. Thakor. (2005) "Financial Intermediation as a Beliefs-Bridge between Optimists and Pessimists." *Journal of Financial Economics* 75, 535–569.

Crone, S. F. (2002) "Training artificial neural networks for time series prediction using asymmetric cost functions." In ICONIP '02. Proceedings of the 9th International Conference on Neural Information Processing, vol. 5, pp. 2374–2380.

Crone, S. F. (2003) "Prediction of white noise time series using artificial neural networks and asymmetric cost functions." In Proceedings of the International Joint Conference on Neural Networks, 2003, vol. 4, pp. 2460–2465.

Crone, S. F. (2010) *Neuronale Netze zur Prognose und Disposition im Handel.* Wiesbaden: Betriebswirtschaftlicher Verlag Th. Gabler.

Crone, Sven F. and Nikolaos Kourentzes. (2010) “Feature selection for time series prediction – A combined filter and wrapper approach for neural networks.” *Neurocomputing* 73, 1923–1936.

De Nicoló, Gianni. (2000) *Size, Charter Value and Risk in Banking: An International Perspective.* Working paper, Board of Governors of the Federal Reserve System.

De Nicoló, Gianni, Philip Bartholomew, Jahanara Zaman and Mary Zephirin. (2004) “Bank Consolidation, Internationalization, and Conglomeration: Trends and Implications for Financial Risk.” *Financial Markets, Institutions and Instruments* 13, 173–217.

Deep, Akash and Guido Schaefer. (2004) *Are Banks Liquidity Transformers?* Working paper, John F. Kennedy School of Government.

Delgado, Francisco J. (2005) “Measuring Efficiency with Neural Networks: An Application to the Public Sector.” *Economics Bulletin* 3, 1–10.

Delis, Manthos D. and Efthymios G. Tsionas. (2009) “The Joint Estimation of Bank-Level Market Power and Efficiency.” *Journal of Banking & Finance* 33, 1842–1850.

Demerjian, Peter, Baruch Lev and Sarah McVay. (2012) “Quantifying Managerial Ability: A New Measure and Validity Tests.” *Management Science* 58, 1229–1248.

Dewatripont, M. and E. Maskin. (1995) “Credit and Efficiency in Centralized and Decentralized Economies.” *The Review of Economic Studies* 62, 541–555.

DeYoung, Robert, Kenneth Spong and Richard J. Sullivan. (2001) “Who’s minding the store? Motivating and monitoring hired managers at small, closely held commercial banks.” *Journal of Banking & Finance* 25, 1209–1243.

Diamond, Douglas W. and Philip H. Dybvig. (1983) “Bank Runs, Deposit Insurance, and Liquidity.” *Journal of Political Economy* 91, 401–419.

Diamond, Douglas W. and Raghuram G. Rajan. (2000) “A Theory of Bank Capital.” *Journal of Finance* 55, 2431–2465.

Diamond, Douglas W. and Raghuram G. Rajan. (2001) “Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking.” *Journal of Political Economy* 109, 287.

Duchin, Ran, Oguzhan Ozbas and Berk A. Sensoy. (2010) “Costly external finance, corporate investment, and the subprime mortgage credit crisis.” *Journal of Financial Economics* 97, 418–435.

Dwyer, Gerald P. and Paula Tkac. (2009) “The financial crisis of 2008 in fixed-income markets.” *Journal of International Money and Finance* 28, 1293–1316.

Eisenhardt, Kathleen M. and Claudia Bird Schoonhoven. (1990) “Organizational Growth: Linking Founding Team, Strategy, Environment, and Growth Among U.S. Semiconductor Ventures, 1978-1988.” *Administrative Science Quarterly* 35, 504–529.

Emrouznejad, Ali and Estelle Shale. (2009) “A combined neural network and DEA for measuring efficiency of large scale datasets.” *Computers & Industrial Engineering* 56, 249–254.

Fama, Eugene F. and Kenneth R. French. (1993) “Common Risk Factors in the Returns on Stock and Bonds.” *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French. (1997) "Industry costs of equity." *Journal of Financial Economics* 43, 153–193.

Fan, Yanqin, Qi Li and Alfons Weersink. (1996) "Semiparametric Estimation of Stochastic Production Frontier Models." *Journal of Business & Economic Statistics* 14, 460–468.

Farrell, M. J. (1957) "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society. Series A (General)* 120, 253–290.

Federal Deposit Insurance Corporation. (2012) *Summary of Deposits Database.* URL: `http://www2.fdic.gov/sod/`. Visited on: 01.03.2012.

Federal Reserve Bank of San Francisco. (1999) *Using CAMELS Ratings to Monitor Bank Conditions.* URL: `http://www.frbsf.org/econrsrch/wklyltr/wklyltr99/el99-19.html`. Visited on: 30.04.2013.

Feng, Guohua and Apostolos Serletis. (2009) "Efficiency and Productivity of the US Banking Industry, 1998-2005: Evidence from the Fourier Cost Function Satisfying Global Regularity Conditions." *Journal of Applied Econometrics* 24, 105–138.

Feng, Guohua and Apostolos Serletis. (2010) "Efficiency, Technical Change, and Returns to Scale in Large US Banks: Panel Data Evidence from an Output Distance Function Satisfying Theoretical Regularity." *Journal of Banking & Finance* 34, 127–138.

Fethi, Meryem Duygun and Fotios Pasiouras. (2010) "Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey." *European Journal of Operational Research* 204, 189–198.

Fiordelisi, Franco. (2007) "Shareholder value efficiency in European banking." *Journal of Banking & Finance* 31, 2151–2171.

Fiordelisi, Franco and Phil Molyneux. (2007) *Shareholder value and the clash in performance measurement: are banks special?* Working paper, University of Wales Bangor, Centre for Banking and Finance, UK.

Fiordelisi, Franco and Phil Molyneux. (2010) "The determinants of shareholder value in European banking." *Journal of Banking & Finance* 34, 1189–1200.

Flannery, Mark J., Simon H. Kwan and Mahendrarajah Nimalendran. (2013) "The 2007-2009 financial crisis and bank opaqueness." *Journal of Financial Intermediation* 22, 55–84.

Gallant, A. Ronald. (1981) "On the bias in flexible functional forms and an essentially unbiased form: The fourier flexible form." *Journal of Econometrics* 15, 211–245.

Gallant, A. Ronald. (1982) "Unbiased determination of production technologies." *Journal of Econometrics* 20, 285–323.

Ge, Weili, Dawn Matsumoto and Jenny Li Zhang. (2011) "Do CFOs Have Style? An Empirical Investigation of the Effect of Individual CFOs on Accounting Practices." *Contemporary Accounting Research* 28, 1141–1179.

Gnecco, Giorgio and Marcello Sanguineti. (2009) "The Weight-Decay Technique in Learning from Data: An Optimization Point of View." *Computational Management Science* 6, 53–79.

Good, David H, M Ishaq Nadiri, Lars-Hendrik Röller and Robin C Sickles. (1993) "Efficiency and productivity growth comparisons of European and US air carriers: a first look at the data." *The Journal of Productivity Analysis* 4, 115–125.

Granger, C. W. J. (1969) "Prediction with a Generalized Cost of Error Function." *Operational Research Quarterly* 20, 199–207.

Graves, Alex, Abdel rahman Mohamed and Geoffrey Hinton. (2013) "Speech recognition with deep recurrent neural networks." In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, pp. 6645–6649.

Graves, Alex and Jürgen Schmidhuber. (2005) "Framewise phoneme classification with bidirectional LSTM and other neural network architectures." *Neural Networks* 18, 602–610.

Guermat, C. and K. Hadri. (1999) *Misspecification in Stochastic Frontier Models. Backpropagation Neural Networks Versus Translog Model: A Monte Carlo Comparison.* Working paper, University of Exeter.

Hambrick, Donald C. (2007) "Upper Echelons Theory: an Update." *Academy of Management Review* 32, 334–343.

Hambrick, Donald C. and Phyllis A. Mason. (1984) "Upper Echelons: The Organization as a Reflection of Its Top Managers." *The Academy of Management Review* 9, 193–206.

Hancock, Diana. (1985) "The Financial Firm: Production with Monetary and Nonmonetary Goods." *Journal of Political Economy* 93, 859–880.

Hausman, J. A. (1978) "Specification Tests in Econometrics." *Econometrica* 46, 1251–1271.

Haykin, Simon S. (1999) *Neural networks: a comprehensive foundation.* 2nd edition. New York, London: Macmillan.

Hinton, G. and R. R. Salakhutdinov. (2006) "Reducing the dimensionality of data with neural networks." *Science* 313, 504–507.

Hornik, Kurt, Maxwell Stinchcombe and Halbert White. (1989) "Multilayer feedforward networks are universal approximators." *Neural Networks* 2, 359–366.

Huang, Tai-Hsin and Mei-Hui Wang. (2002) "Comparison of Economic Efficiency Estimation Methods: Parametric and Non-parametric Techniques." *Manchester School* 70, 682–709.

Hughes, Joseph P., William W. Lang, Loretta J. Mester, Choon-Geol Moon and Michael S. Pagano. (2003) "Do bankers sacrifice value to build empires? Managerial incentives, industry consolidation, and financial performance." *Journal of Banking & Finance* 27, 417–447.

Jenkins, Patrick and Adam Jones. (2012) *Lloyds shrinks mortgage lending.* URL: `http://www.ft.com/cms/s/0/ae862572-9308-11e1-aa60-00144feab49a.html#axzz22yINovuD`. Visited on: 08.08.2012.

Jensen, Michael C. and William H. Meckling. (1976) "Theory of the firm: Managerial behavior, agency costs and ownership structure." *Journal of Financial Economics* 3, 305–360.

Jondrow, James, C. A. Knox Lovell, Ivan S. Materov and Peter Schmidt. (1982) "On the estimation of technical inefficiency in the stochastic frontier production function model." *Journal of Econometrics* 19, 233–238.

Jones, Jeffrey S., Wayne Y. Lee and Timothy J. Yeager. (2012) "Opaque banks, price discovery, and financial instability." *Journal of Financial Intermediation* 21, 383–408.

Kao, Chiang and Shiang-Tai Liu. (2004) "Predicting Bank Performance with Financial Forecasts: A Case of Taiwan Commercial Banks." *Journal of Banking & Finance* 28, 2353–2368.

Kao, Chiang and Shiang-Tai Liu. (2009) "Stochastic data envelopment analysis in measuring the efficiency of Taiwan commercial banks." *European Journal of Operational Research* 196, 312–322.

Khanna, Naveen and Annette B. Poulsen. (1995) "Managers of Financially Distressed Firms: Villains or Scapegoats?" *Journal of Finance* 50, 919–940.

Kneip, Alois, Léopold Simar and Paul W. Wilson. (2008) "Asymptotics and Consistent Bootstraps for DEA Estimators in Nonparametric Frontier Models." *Econometric Theory* 24, 1663–1697.

Kumbhakar, Subal and C. A. Knox Lovell. (2003) *Stochastic frontier analysis.* Cambridge: Cambridge University Press.

Leverty, J. Tyler and Martin F. Grace. (2012) "Dupes or Incompetents? An Examination of Management's Impact on Firm Distress." *Journal of Risk & Insurance* 79, 751–783.

McAllister, Patrick H. and Douglas McManus. (1993) "Resolving the scale efficiency puzzle in banking." *Journal of Banking & Finance* 17, 389–405.

Mester, Loretta J. (1993) "Efficiency in the savings and loan industry." *Journal of Banking & Finance* 17, 267–286.

Mester, Loretta J. (1996) "A study of bank efficiency taking into account risk-preferences." *Journal of Banking & Finance* 20, 1025–1045.

Michaelides, Panayotis G., Angelos T. Vouldis and Efthymios G. Tsionas. (2010) "Globally flexible functional forms: The neural distance function." *European Journal of Operational Research* 206, 456–469.

Miles, James A. and John R. Ezzell. (1980) "The Weighted Average Cost of Capital, Perfect Capital Markets and Project Life: A Clarification." *Journal of Financial & Quantitative Analysis* 15, 719–730.

Mitchell, Janet. (2001) "Bad Debts and the Cleaning of Banks' Balance Sheets: An Application to Transition Economies." *Journal of Financial Intermediation* 10, 1–27.

Mitchell, Karlyn and Nur M. Onvural. (1996) "Economies of Scale and Scope at Large Commercial Banks: Evidence from the Fourier Flexible Functional Form." *Journal of Money, Credit & Banking* 28, 178–199.

Monnet, Cyril and Erwan Quintin. (2013) *Rationally Opaque Intermediaries.* Working paper.

Morgan, Donald P. (2002) "Rating Banks: Risk and Uncertainty in an Opaque Industry." *The American Economic Review* 92, 874–888.

Myers, Stewart C. (2001) "Capital Structure." *Journal of Economic Perspectives* 15, 81–102.

Myers, Stewart C. and Raghuram G. Rajan. (1998) "The Paradox of Liquidity." *Quarterly Journal of Economics* 113, 733–771.

New York Federal Reserve Bank. (2012) *CRSP-FRB Link.* URL: `http://www.newyorkfed.org/research/banking_research/datasets.html`. Visited on: 10.10.2012.

Ng, Andrew, Jiquan Ngiam, Chuan Yu Foo, Yifan Mai and Caroline Suen. (2011) *UFLDL Tutorial.* URL: `http://ufldl.stanford.edu/wiki/index.php/Backpropagation_Algorithm`. Visited on: 01.10.2011.

Nguyen, D. and B. Widrow. (1990) "Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights." In 1990 IJCNN International Joint Conference on Neural Networks, pp. 21–26.

Nixon, Simon. (2013) *Financial Innovation is Suddenly Back in Fashion.* URL: `http://online.wsj.com/article/SB10001424127887324549004579062742710983288.html`. Visited on: 09.09.13.

O'Donnell, Svenja. (2012) *U.K. Mortgage Lending Declines, Construction Shrinks: Economy.* URL: `http://www.bloomberg.com/news/2012-07-03/u-k-mortgage-lending-declines-construction-shrinks-economy.html`. Visited on: 03.07.2012.

Parekh, Rajesh, Jihoon Yang and Vasant Honavar. (2000) "Constructive neural-network learning algorithms for pattern classification." *IEEE Transactions on Neural Networks* 11, 436–451.

Pendharkar, Parag C. and James A. Rodger. (2003) "Technical efficiency-based selection of learning cases to improve forecasting accuracy of neural networks under monotonicity assumption." *Decision Support Systems* 36, 117–136.

Pi, Lynn and Stephen G. Timme. (1993) "Corporate control and bank efficiency." *Journal of Banking & Finance* 17, 515–530.

Pitt, Mark M. and Lung-Fei Lee. (1981) "The measurement and sources of technical inefficiency in the Indonesian weaving industry." *Journal of Development Economics* 9, 43–64.

Post, Thierry. (2007) "Nonparametric efficiency estimation in stochastic environments: Noise-to-signal estimation, finite sample performance and hypothesis testing." *Journal of Banking & Finance* 31, 2065–2080.

Post, Thierry, Laurens Cherchye and Timo Kuosmanen. (2002) "Nonparametric Efficiency Estimation in Stochastic Environments." *Operations Research* 50, 645–655.

Pritsker, Matthew. (2010) "Informational Easing: Improving Credit Conditions through the Release of Information." *Federal Reserve Bank of New York Economic Policy Review* 16, 77–87.

Rajgopal, Shivaram, Terry Shevlin and Valentina Zamora. (2006) "CEOs' Outside Employment Opportunities and the Lack of Relative Performance Evaluation in Compensation Contracts." *Journal of Finance* 61, 1813–1844.

Rogerson, William P. (1997) "Intertemporal cost allocation and managerial investment incentives: A theory explaining the use of economic value added as a performance measure." *Journal of Political Economy* 105, 770–795.

Ross, Stephen A. (1976) "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory* 13, 341–360.

Rumelhart, David E. and James L. McClelland. (1986) *Parallel distributed processing: explorations in the micro-structure of cognition.* Cambridge, Mass., London: MIT Press.

Santín, Daniel. (2008) "On the approximation of production functions: a comparison of artificial neural networks frontiers and efficiency techniques." *Applied Economics Letters* 15, 597–600.

Santín, Daniel, Francisco J. Delgado and Aurelia Valiño. (2004) "The measurement of technical efficiency: a neural network approach." *Applied Economics* 36, 627–635.

Sealey, C. W. and James T. Lindley. (1977) "Inputs, Outputs and a Theory of Production and cost at Depository Financial Institutions." *Journal of Finance* 32, 1251–1266.

Sharpe, William F. (1964) "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *Journal of Finance* 19, 425–442.

Shen, Chung-Hua and Hsiang-Lin Chih. (2005) "Investor protection, prospect theory, and earnings management: An international comparison of the banking industry." *Journal of Banking & Finance* 29, 2675–2697.

Simar, Léopold and Paul W. Wilson. (1998) "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models." *Management Science* 44, 49–61.

Simar, Léopold and Paul W. Wilson. (2007) "Estimation and inference in two-stage, semi-parametric models of production processes." *Journal of Econometrics* 136, 31–64.

Simar, Léopold and Paul W. Wilson. (2000) "A general methodology for bootstrapping in non-parametric frontier methods." *Journal of Applied Statistics* 27, 779–802.

Stone, Bernell K. (1974) "Systematic Interest-Rate Risk in a Two-Index Model of Returns." *Journal of Financial & Quantitative Analysis* 9, 709–721.

Thakor, Anjan V. (2005) "Do Loan Commitments Cause Overlending?" *Journal of Money, Credit & Banking* 37, 1067–1099.

The Tax Foundation. (2012) *State Corporate Income Tax Rates, 2000-2012.* URL: `http://taxfoundation.org/article/state-corporate-income-tax-rates`. Visited on 15.03.2012.

Tregenna, Fiona. (2009) "The Fat Years: The Structure and Profitability of the US Banking Sector in the Pre-crisis Period." *Cambridge Journal of Economics* 33, 609–632.

Ünal, Haluk and Edward J. Kane. (1988a) "Change in Market Assessments of Deposit-Institution Riskiness." *Journal of Financial Services Research* 1, 207–229.

Ünal, Haluk and Edward J. Kane. (1988b) "Two Approaches to Assessing the Interest Rate Sensitivity of Deposit Institution Equity Returns." *Research in Finance* 7, 113–137.

Uyemura, Dennis G., Charles C. Kantor and Justin M. Pettit. (1996) "EVA® for Banks: Value Creation, Risk Management, and Profitability Measurement." *Journal of Applied Corporate Finance* 9, 94–109.

Vouldis, Angelos T., Panayotis G. Michaelides and Efthymios G. Tsionas. (2010) "Estimating semi-parametric output distance functions with neural-based reduced form equations using LIML." *Economic Modelling* 27, 697–704.

Wang, Shouhong. (2003) "Adaptive non-parametric efficiency frontier analysis: a neural-network-based model." *Computers & Operations Research* 30, 279–295.

Watts, Ross L. and Luo Zuo. (2012) *Accounting Conservatism and Firm Value: Evidence from the Global Financial Crisis.* Working paper, Massachusetts Institute of Technology.

Weill, Laurent. (2004) "Measuring Cost Efficiency in European Banking: A Comparison of Frontier Techniques." *Journal of Productivity Analysis* 21, 133–152.

Werbos, Paul J. (1974) "Beyond regression: New tools for prediction and analysis in the behavioral sciences." PhD thesis. Harvard University.

Wheelock, David C. and Paul W. Wilson. (2001) "New evidence on returns to scale and product mix among U.S. commercial banks." *Journal of Monetary Economics* 47, 653–674.

White, Halbert. (1992) "Nonparametric Estimation of Conditional Quantiles Using Neural Networks." In *Computing Science and Statistics,* edited by Page, Connie and Raoul LePage, pp. 190–199. New York: Springer.

Wu, Desheng, Zijiang Yang and Liang Liang. (2006) "Using DEA-neural network approach to evaluate branch efficiency of a large Canadian bank." *Expert Systems with Applications* 31, 108–115.

Yang, Jianchao, Kai Yu, Yihong Gong and Thomas Huang. (2009) "Linear spatial pyramid matching using sparse coding for image classification." In IEEE Conference on Computer Vision and Pattern Recognition, 2009, IEEE, pp. 1794–1801.

Zhang, G. Peter. (2007) "A neural network ensemble method with jittered training data for time series forecasting." *Information Sciences* 177, 5329–5346.